Lightweight Performance Forecasts for Buffer Algorithms

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Abstract: Buffer memory allocation is one of the most important, but also one of the most difficult tasks of database system administration. Typically, database management systems use several buffers simultaneously for various reasons, e.g., disk speed, page size, access behavior. As a result, available main memory is partitioned among all buffers within the system to suit the expected workload, which is a highly complex optimization problem. Even worse, a carefully adjusted configuration can become inefficient very quickly on workload shifts. Self-tuning techniques automatically address this allocation problem using periodic adjustments of buffer sizes. The tuning itself is usually achieved by changing memory (re-)allocations based on hit/miss ratios, thereby aiming at minimization of I/O costs. All techniques proposed so far observe or simulate the buffer behavior to make forecasts whether or not increased buffer sizes are beneficial. However, database buffers do not scale uniformly (i.e., in a linear fashion) and simple extrapolations of the current performance figures can easily lead to wrong assumptions. In this work, we explore the use of lightweight extensions for known buffer algorithms to improve the forecast quality by identifying the effects of varying buffer sizes using simulation. Furthermore, a simple cost model is presented to optimize dynamic memory assignments based on these forecast results.

1 Introduction

Dynamic database management gained a lot of attention and visibility during recent years and led to various self-tuning approaches. As I/O reduction is one of the most important aspects, automatized buffer memory management has always been one of the building blocks for (self-)tuning of database systems. Data placement decisions but also variations in access patterns, page sizes, access speed, read/write characteristics, or prices of storage devices suggest the support of multiple buffers to optimally exploit existing I/O bandwidth. Memory partitioning, however, frequently entails memory waste, because some buffers may be underused while others are overused. Here, only continuous monitoring of system performance may assure adequate usage of the total memory budget and regular adjustment of buffer allocations at runtime, thereby enabling minimization of waste.

The decision when and which buffers have to be resized requires a cost-based model together with buffer techniques (i.e., page mapping, propagation algorithm) that are self-tunable at runtime. The quality of a decision depends on the cost model itself and the

accuracy of forecasts. However, database buffers typically scale non-uniformly (i.e., in a non-linear fashion) and simple extrapolations of current performance figures can easily lead to wrong assumptions. In the worst case, the redistribution of buffer memory results in unintended buffer sweeps followed by excessive I/O thrashing, which again increases the time to pour oil on troubled waters. In our opinion, self-tuning components should therefore follow a strict "Don't be evil" policy.

Most tuning approaches aim at maximum speedup, i.e., they focus on the identification of the greatest profiteer when more buffer memory can be assigned. Accordingly, they usually shift memory from buffers having low I/O traffic and/or low potential for performance gains to more promising ones. We believe that a sole focus on buffer growth is dangerous, because the risk of wrong decisions comes mainly from the inaccuracy of forecasts concerning smaller buffers. Once a buffer is shrunk too much, it may cause a lot of I/O and, in this way, also affect the throughput of all remaining buffers. Thus, reliable estimations for buffer downsizing are obviously as important as estimations for buffer upsizing. Good forecast quality is further urgently needed in dynamic environments which have to cope with many or intense workload shifts. Here, too cautious, i.e., too tiny adjustments, even when they are incrementally done, are not good enough to keep the system in a well performing state. Reliable forecasts help to justify more drastic reconfigurations which may be necessary to keep up with workload shifts.

1.1 Forecast of Buffer Behavior

Proposed forecast models for the performance of a resized buffer can be divided into two groups: The first group uses heuristics-based or statistical indicators to forecast buffer hit ratios, whereas the second group is based on simulation. Using heuristics-based approaches, the forecast quality is hard to determine. As a consequence, their use comes with the risk of wrong tuning decisions which may heavily impact system performance. Simulation-based approaches allow trustworthy estimations, but usually only limited to the simulated buffer size. Outside already known or simulated ranges, hit ratios may change abruptly. For this reason, we need forecasts for *growing and shrinking* buffers.

The performance of a buffer does not scale linearly with its pool size, because mixed workloads containing scans and random I/O can cause abrupt jumps in the hit-ratio trend line as ilustrated in Figure 1. These jumps may also lead to differing speed-ups for varying buffer sizes, which again may cause wrong assumptions and decisions.

Performance prediction is always based on information gathered by monitoring, taking samples or (user) hints into account. Hit/miss ratios are the standard quality metrics for buffers, because they are cheap and express the actual goal of buffer use: I/O reduction. Unfortunately, they are useless for performance forecasts, i.e., they even do not allow to make simple extrapolations for growing or shrinking buffer sizes. To illustrate this fact, let us assume the following scenario for a given buffer size of 5 and LRU-based replacement. At the end of a monitoring period, we observed 5 hits and 10 misses. At least two different access patterns may have led to these statistics:

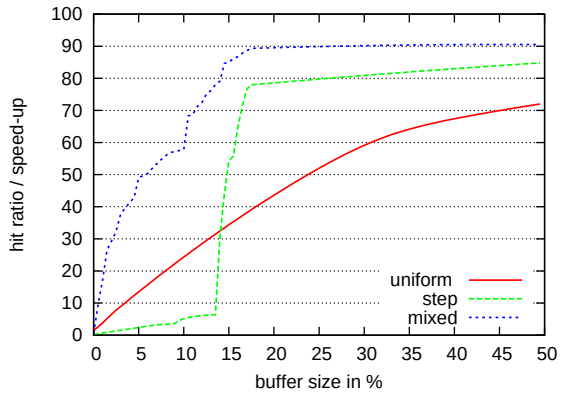


Figure 1: Buffer speed-up trend for different access patterns.

Scenario 1: $1, 2, 3, 4, 5, 1, 1, 1, 1, 1, 6, 7, 8, 9, 10, ...$

Scenario 2: $1, 2, 3, 4, 5, 1, 2, 3, 4, 5, 6, 1, 2, 3, 4, ...$

In the first scenario, 5 hits are attributed to repeated accesses of page 1, whereas, in the second scenario, the hits are attributed to 5 different pages (1, 2, 3, 4, 5). For the same scenarios and a buffer of size 2, we get completely different hit (h) and miss (m) statistics:

Scenario 1: $m, m, m, m, m, m, h, h, h, h, m, m, m, m, m, ...$

Scenario 2: $m, m, m, m, m, m, m, m, m, m, m, m, m, m, m, ...$

Obviously scenario 1 obtains a better hit rate with 4 hits to 11 misses than scenario 2 without any hit. If we increase the buffer instead to hold 6 pages in total, the picture turns again:

Scenario 1: $m, m, m, m, m, h, h, h, h, h, m, m, m, m, m, ...$

Scenario 2: $m, m, m, m, m, h, h, h, h, h, h, h, h, h, h, ...$

Now we observe 5 hits to 10 misses for scenario 1 and 10 hits to 5 misses for scenario 2. This example shows that hit/miss numbers or page/benefit metrics do not allow for correct extrapolations, because the order of page requests and the hit frequency distribution are important. Thus, self-tuning relies on monitoring and sampling of data where current buffer use is taken as an indicator for the future. Information relevant for resizing forecasts such as re-use frequencies, working set size, or noise generated by scans cannot be expressed in single numbers.

Instead, the ideal starting point for buffer forecasts is the replacement algorithm used for a buffer. Its statistics incorporate a lot more information about these relevant aspects than

any other performance marker. Today, substantial research has already been performed to develop adaptive replacement algorithms, hence, it is safe to assume that such algorithms are "optimally" operating for the available memory. The question is now how to leverage this implicit knowledge for performance forecasts. As we will demonstrate in the remainder of this paper, it is difficult but not impossible to get accurate estimates for buffer downsizing. In combination with already known simulation methods for the estimation of buffer upsizing, we can then build a lightweight framework for dynamic buffer management.

1.2 Related Work

Optimal buffer management has been a key aspect in database system research since the very early days. Thus, various aspects such as the underlying disk model, search strategies within a buffer, replacement algorithms, concurrency issues and the implications of the page layout have been intensely studied [EH84]. Nevertheless, the complexity of buffer management did not allow to distill an optimal configuration for all different kinds of workloads and system environments. Instead, self-tuning mechanisms were explored to resolve performance bottlenecks at runtime.

One early self-tuning approach hints at specific access patterns like scans or index traversals to the buffer to optimize victim selection [JCL90]. This allows to outperform standard LRU-based algorithms but addresses only a single aspect of dynamic buffer management. In [NFS95], the authors give a theoretical base for the combined analysis of buffer sizing decisions and the influence of access patterns. [Dia05] models buffer load balancing as a constrained optimization problem and investigates the application of control theory and optimization theory.

In [SGAL+06], control theory, runtime simulation, and cost-benefit analysis are integrated into a self-tuning framework. The presented forecast technique SBPX serves also as our baseline and is introduced in detail in Section 2. Some heuristic forecast techniques are presented in [BCL93, MLZ+00]. The analytical work in [THTT08] derives an equation to relate miss probability to buffer allocation. Finally, [DTB09] proposes a brute-force step-by-step approach to determine the optimal configuration for an entire DBMS.

1.3 Contribution

In this work, we study two major prerequisites for self-tuning buffer memory allocation: cost determination and decision making. As the main objective of buffer tuning is I/O reduction and main memory management, decisions based on I/O costs are required to efficiently distribute available memory among all buffer pools. In particular, we look at overhead and quality for buffer undersizing and oversizing forecasts to estimate I/O costs for alternative configurations.

We present ideas to integrate low-overhead forecast capabilities for several common buffer algorithms and assess their feasibility in experiments. Furthermore, we show how these forecasts can be used for nearly riskless self-tuning decisions. Eventually, a short evaluation is revealing prospects of simulation-based buffer tuning as well as its limitations.

The remainder of this paper is organized as follows: Sections 2 and 3 discuss forecast techniques for buffer upsizing and downsizing, respectively. In Section 4, we present a decision model for a self-tuning component. The results of our experiments are shown in Section 5. Finally, Section 6 concludes the paper.

2 Forecast of Buffer Upsizing

The obvious way of accounting I/O costs for alternative buffer sizes is to fully simulate each of them for the same page reference string, i.e., page request sequence. Of course, a simulation of the propagation behavior for page numbers is sufficient; the actual payload data need not be kept in memory. Nevertheless, this approach requires additional data structures, such as hash maps for lookup, lists for the replacement algorithm, and virtual pages. Moreover, each buffer request has to be processed multiple times, i.e., page lookup and replacement maintenance for each simulated configuration. Obviously, the overhead of such a solution is prohibitive. In contrast, cheaper solutions may be less accurate, but still achieve meaningful results for resizing decisions.

Our buffer self-tuning refinements are inspired by the SBPX framework [SGAL$^+$06], which approximates the benefit of a larger buffer through "buffer extension". This extension is simply an overflow buffer for the page identifiers of the most recently evicted pages. The overflow buffer must, of course, have its own strategy for victimization. The authors of SBPX recommend here a strategy "similar to that of the actual buffer pool" [SGAL$^+$06].

When a page miss in the actual buffer occurs, the extension checks if the page identifier is found in the overflow buffer, i.e., if the page would have been present in a larger buffer. In that case, we can account a "savings" potential for upsizing. Further, we must now maintain the overflow buffer. The page identifier of the actual evicted page is promoted to the overflow buffer, which in general requires to evict another page identifier from the overflow buffer. This replacement is not exactly the same as a real miss in the simulated larger buffer. The identifier of the requested page causing the miss could have been present in the larger buffer. In the course of continuous requests, however, also a larger buffer must evict pages. Thus, a replacement in the overflow buffer can be regarded as a "delayed" replacement effect. In the case of a page hit in the actual buffer, no further bookkeeping is required, because the locality principle suggests that the replacement strategy in a larger buffer holds a superset of the pages present in a smaller one. Listing 1 shows a sketch of the modified page fix routine.

The problem of this approach is that replacement decisions for two separate buffers in combination are not necessarily the same as for a single large buffer. Thus, the forecast quality of upsizing simulations depends on one aspect: When a page is evicted from the

actual buffer and promoted to the overflow area, we must be able to transfer "state" information (e.g., hit counters, chain position, etc.) from the actual replacement strategy into the overflow strategy (lines 17 and 20). Otherwise, the overflow strategy behaves differently.

Listing 1: Modified page fix algorithm for upsize simulation

```
1 Frame fix(long pageNo) {
2   Frame f = mapping.lookup(pageNo);
3   if (f != null) {
4     strategy.refer(f);                  // update replacement strategy
5     ...                                 // and statistics
6   } else {
7     Frame of = overflowMapping.lookup(pageNo);
8     if (of != null) {
9       overflowMapping.remove(of.pageNo);
10      ...                               // update overflow hit statistics
11    } else {
12      of = overflowStrategy.victim();
13      overflowBuffer.remove(of.pageNo);
14      ...                               // update overflow miss statistics
15    }
16
17    Frame v = strategy.chooseVictim();
18    strategy.copyStateTo(overflowStrategy);
19
20    v.copyStateTo(of);                  // transfer page identifier to overflow
21    overflowMapping.put(of.pageNo, of);
22
23    mapping.remove(v.pageNo);
24    ...                                 // replace page in frame v
25    strategy.referAsNew(v);             // update replacement strategy
26    ...                                 // and statistics
27    mapping.put(pageNo, v);
28  }
29 }
```

3 Forecast of Buffer Downsizing

As shown above, knowledge about the performance gain through a larger buffer is useful to determine the greatest profiteer of more memory among several buffers. However, the question for the buffer(s), which may be safely shrunk without suffering from severe penalties, remains unanswered. The authors of SBPX extrapolated downsizing costs as the inverse of savings potential gained through upsizing [SGAL$^+$06]. For buffer sizes close to the unknown (!) borders of working set sizes, however, this bears the risk of wrong decisions. Therefore, we developed a simple mechanism to find out if page hits would have been also page hits in a smaller buffer. In combination, the SBPX technique allows us now to determine which buffer profits the most from additional memory, while our approach helps us to determine which buffer suffers least from downsizing.

The goal of buffer replacement algorithms is the optimized utilization of data access locality, i.e., to keep the set of the currently hottest pages that fits into memory. Accordingly, a small buffer is assumed to keep an "even hotter subset" of the pages that would be present in the actual buffer. Based on this assumption, we denote a subset of the pages in a buffer

of size n as $hotset_k$, if it would be kept in a smaller buffer of size k. The key idea of our approach is to keep track of this hotset during normal processing. When a page is found in the buffer and belongs to the hotset, it would have been a hit in the smaller buffer, too. However, if a requested page is in the current buffer but not in the hotset, the smaller buffer would need to evict another page, which must be, of course, part of the current hotset and load the requested page from disk. Here, we only have to maintain the hotset. The page that would have been evicted from the smaller buffer is removed from the hotset and the requested page is added to the hotset. Each swap is accounted as a page miss for the simulated smaller buffer.

Of course, a page miss in the current buffer would also be a page miss in a smaller buffer. Accordingly, we have to select a replacement victim for both the current buffer and the (simulated) smaller buffer. The real victim page is now replaced with the new page and swapped with the virtual victim of the smaller buffer into the hotset. The modified page fix algorithm is shown in Listing 2.

Listing 2: Modified page fix algorithm for downsize simulation

```
1 Frame fix(long pageNo) {
2   Frame f = mapping.lookup(pageNo);
3   if (f != null) {
4     if (!f.hotSet) {
5       Frame v = strategy.chooseHotSetVictim();
6       f.hotset = true;                  // swap frame to hotset
7       v.hotset = false;
8       strategy.swapHotset(f, v);
9       ...                               // update simulated statistics
10    }
11    strategy.refer(f);                  // update replacement strategy
12    ...                                 // and statistics
13  } else {
14    Frame v = strategy.chooseVictim();
15    mapping.remove(v.pageNo);
16    ...                                 // replace page in frame v
17    if (!v.hotset) {
18      Frame hv = strategy.chooseHotSetVictim();
19      hv.hotSet = false;                // swap frame to hotset
20      v.hotSet = true;
21      strategy.swapHotset(f, v);
22    }
23    strategy.referAsNew(v);             // update replacement strategy
24    ...                                 // and statistics
25    mapping.put(pageNo, v);
26  }
27 }
```

Note that a real replacement victim is generally not expected to be part of the current hotset, because this would imply that the replacement strategy evicts a page more recently accessed. In some algorithms, however, such counter-intuitive decisions might be desired, e.g., to explicitly rule out buffer sweeps through large scans. Then, we must not maintain the hotset at all.

Obviously, the overhead of this approach is very small. We only need a single bit per buffer frame to flag the hotset membership and must determine a swap partner, when a new page enters the hotset. Furthermore, the simulation does not influence the quality of the current buffer, i.e., the strength of the replacement strategy is fully preserved. As said, the choice of the hotset victim is dependent on the used replacement strategy to reflect the behavior of

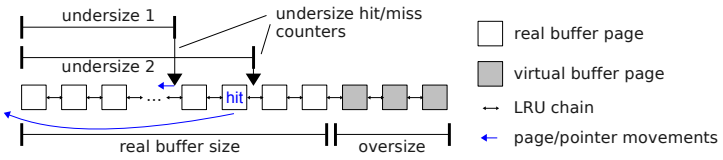


Figure 2: LRU-based buffer simulation with overflow extension

the strategy in a smaller buffer correctly. In the following, we will investigate hotset victim determination for four popular families of replacement algorithms. In particular, we want to know if it is possible to predict replacement decisions for a smaller buffer based on the implicit knowledge present.

3.1 LRU

The LRU algorithm embodies a very simple, yet effective replacement strategy. It evicts always the *least recently used* page from a buffer. Typically, it is implemented as a doubly-linked list as shown in Figure 2.

On request, a page is simply put to the head of the chain. Thus, LRU finds its replacement candidate always at the tail. Accordingly, the last k pages of the LRU chain in a larger buffer of size n are identical with the k pages in the simulated smaller buffer of size k and the hotset victim page is found at the k-th position from the head. The overhead of pointer dereferencing to position k can be avoided with marker pointer, which is cheap to maintain. Hence, the hotset victim is guaranteed to be identical to the victim as in the smaller buffer and the simulation is fully precise. Evidently, the simplicity of LRU even allows to easily simulate at the same time the effects when the current buffer would be reduced to different smaller sizes, which is especially useful for precise step-wise tuning decisions. It is sufficient to place a marker at each desired position.

3.2 LRU-K

The LRU-K algorithm [OOW99] follows a more general idea of LRU and takes the last K references of a page into account. By doing so, it is "scan-resistant" and less vulnerable to workloads where frequently re-used pages mix with those having hardly any rereference. For each page, LRU-K maintains a history vector with the last K references and the timestamp of its last reference. Furthermore, history vectors of already evicted pages are retained for re-use if an evicted page is requested again within the so-called *retained information period* (RIP). The replacement victim is only searched among those pages that have been buffered for at least a predefined *correlated reference period* (CIP). The rationale behind this idea is to prevent a drop of pages immediately after their first reference. For further details on CIP, history maintenance, etc., we refer to the original paper.

The victim page is determined by the maximum backward K-distance, i.e., the page with the earliest reference in the history vector. Thus, although implemented differently, LRU-K behaves for $K = 1$ the same as LRU. The hotset victim is chosen accordingly as shown in Listing 3. Note that implementations of LRU-K usually maintain a search tree for that. For simplicity, we present here the modification of the unoptimized variant as in the original paper.

Due to the history update algorithm described in [OOW99], more than one victim candidate can exist. This could become a problem for our simulation, because a real buffer might choose a different victim than simulated. Therefore, we simply evict the candidate with the least recent reference (line 12). As the timestamp of the last access is unique, our simulation will be accurate here. Instead, the choice of RIP turns out to become a problem. If the garbage collection for history entries is not aligned, pages that re-enter the smaller buffer will be initialized differently than in simulation, which may affect future replacement decisions.

Listing 3: LRU-K hotset victim selection

```
1 Frame hotSetVictim() {
2   long min = t;
3   long minLast = Long.MAX_VALUE;
4   Frame v = null;
5   for (int i = 0; i < pages.length; i++) {
6     Frame p = pages[i];
7     History h = p.history;
8     if ((p.hotSet) && (t - last > CIP)) {
9       long last = h.last;
10      long dist = h.vector[k - 1];
11      if ((dist < min)
12          || ((dist == min) && (last < minLast))) {
13        victim = p;
14        min = hist.vector[k -1];
15      }
16    }
17  }
18  return v;
19 }
```

3.3 GCLOCK

The third strategy is GCLOCK [NDD92], which stands for *generalized clock* algorithm. Like LRU-K, it takes the reference history of a page into account. In contrast to LRU-K, however, it is likely to degrade through scans but can be implemented with less computational and space overhead. The buffer itself is modeled as a circle of buffer frames, i.e., the clock. Each frame also maintains a simple reference counter, which is incremented for each reference to that specific page. For victim selection, the "clock hand" circles over all frames and decrements the reference counters. The clock hand stops at the first frame where the reference counter drops below zero. So, frequently referenced pages remain longer in the buffer, because they have higher reference counts.

The determination of a hotset victim is straightforward: We simply have to circle over the frames and look for the first hotset page whose reference counter would first drop below zero. Obviously, this is the page with the minimum reference counter. The algorithm is sketched in Listing 4.

Listing 4: GCLOCK hotset victim selection

```
1 Frame chooseHotSetVictim()
2 {
3   Frame v = null;
4   int h = clockHand;
5   for (int i = 0; i < size; i++) {
6     Page p = circle[(++h % size)];
7     if (p.hotSet) {
8       if (p.count == 0) {
9         return v;
10      } else if ((v == null) || (p.count < v.count)) {
11        v = p;
12      }
13    }
14  }
15  return v;
16 }
```

Again, this only approximates the behavior of a smaller buffer with GCLOCK. There are two reasons: First, the angular velocity of the clock hand in a smaller buffer is higher because there are less frames. Second, the circular arrangement of buffer frames makes the algorithm inherently dependent on the initial order. Thus, victim selection is not only a matter of the page utilization, but also a matter of clock-hand position and neighborship of frames. Using a second clock hand (i.e., pointer) walking solely over the hotset frames is necessary to address differing round trips. However, swapping of frame positions when the hotset is maintained would impact behavior of GCLOCK in the actual buffer – a circumstance, we want to avoid. To improve forecast quality, we implemented the smaller circle, i.e., the hotset, with forward pointers for hotset pages that point to the logical next one. In case of swapping (see lines 8 an 21 in Listing 2), only the forward pointer and a hotset counter for that page need to be maintained. In Section 5, we will show that these minor efforts can lead to almost perfect estimations.

3.4 2Q

The 2Q algorithm [JS94] is a simplified way of imitating LRU-2, which is noted for delivering good hit ratios but often poor performance due to its complex algorithm. In essence, 2Q is a combination of FIFO and LRU. On the first reference, 2Q places a page in a FIFO queue (denoted $a1$). The first re-reference of a page in the $a1$ queue promotes it to the LRU chain (denoted am). The effect of these two "stages" is that only hot pages are promoted to the LRU chain, which tends to keep cold pages longer than necessary. These cold pages, i.e., pages that are accessed only once within a longer time period are now dropped earlier by the FIFO queue. An extended version of 2Q splits the FIFO queue to keep track of rereferences to pages evicted from the FIFO queue [JS94]. The effect is similar to the history caching of LRU-K and comes with queue sizing problems for forecasts, too.

Sizing problems also arise for the FIFO queue and the LRU chain in the standard algorithm. Therefore, we used a simplified variation of 2Q where all buffer frames are assigned to the LRU chain and the FIFO queue only stores references to the pages in the LRU chain. So, it serves like an index for the LRU chain to identify pages referenced only once so far. Victims are primarily selected from the FIFO queue to replace those pages earlier. A subtlety of 2Q is here that the FIFO queue must not be drained to give new pages a chance for rereference and promotion to the LRU chain. The minimum fill degree of the FIFO queue is a configurable threshold. For simulation, we must therefore count the number of hotset entries in the queue, to be able to decide when a smaller buffer would pick a victim from the FIFO queue and not from the LRU chain. Also, the threshold must be the same for both sizes. Although this results in uniform retention times within the FIFO queue for differing LRU chain sizes, it is acceptable to some degree, because the threshold models the granted window for references of new pages. The hotset victim selection is sketched in Listing 5.

Listing 5: 2Q hotset victim selection

```
1 Frame chooseHotSetVictim()
2 {
3   Frame v;
4   if ((a1.numberOfHotsetEntries() > threshold)) {
5     v = a1.head();
6     while (!v.hotSet) v = v.a1Next;      // Follow FIFO queue to first hotset page
7   } else {
8     v = am.head();
9     while (!v.hotSet) v = v.amNext;      // Follow LRU chain to first hotset page
10  }
11  return v;
```

4 Buffer Tuning

The crucial point in database tuning is the difficulty to precisely predict how a tuning decision will affect system performance. Even experienced database administrators with a deep knowledge of the workload and the database product itself regularly face this challenge. They rely on the assistance of sophisticated monitoring tools to prevent negative effects of their tuning decisions on the production system. Often they also run several observe-analyze-adjust cycles with reference workloads beforehand on dedicated test systems. Of course, this is time-consuming and expensive. Built-in self-monitoring and tuning components can ease this dilemma and reduce the risk of wrong decisions through rather small but continuous and incremental adjustments. In dynamic environments, however, those mechanisms may react too slow to keep up with the rate of workload shifts or short-term resource allocation for higher-level tuning decisions like auto-indexing. Therefore, we aim towards a re-formulation of the central question of automatic tuning from "Which adjustment *certainly will* give the greatest performance benefit?" to "Which adjustment *most likely will* give a performance benefit *but certainly not* result in a performance penalty?". In other words, when we know that our reconfigurations will not harm, we get the freedom to try quicker and more aggressive tuning options.

In general, the total amount of buffer memory is limited and so the decision to assign more memory to a certain buffer is directly coupled with the decision of taking this memory from one or several others. Fortunately, the performance optimization heuristics for I/O-saving buffers (e.g. data pages, sorting) is straightforward: The more main memory can be used the better. Even an oversized buffer, i.e., a buffer larger than the actual data to be buffered, is less likely to become a performance bottleneck due to bookkeeping overhead. It is just a waste of main memory. The downsizing of a buffer, however, comes along with severe risks: the buffer's locality may drastically decrease and even turn into thrashing causing excessive I/O, which also influences throughput of other buffers. Accordingly, we concentrate on the forecast of the negative effects of memory reallocations and base our tuning decisions not only, as common, on the estimated *benefits*, but also on vindicable forecasts of additional *costs*.

4.1 Cost Model

Automatic tuning needs to derive costs from system state or from system behavior to quantify the quality of the current configuration. Additionally, it also needs to estimate the costs of alternative configurations to allow for comparison. Ideally, these costs comprise all performance-relevant aspects including complex dependencies between system components and future workload demands in a single number to allow for perfect decisions. Clearly, such a perfect cost model does not exist in practice. Instead, costs are typically derived from a mixture of cheaply accounted runtime indicators and heuristics-based or experience-based weight factors. The hope is to reflect at least the correct relationship between alternative setups w.r.t. to performance. The more precise this much weaker requirement can be met, the easier we can identify hazardous tuning decisions before they boomerang on the system.

In contrast to computational costs of a specific algorithm, costs expressing the quality of a buffer are inherently dependent on the current workload. Buffering 5% of the underlying data, for example, can be an optimal use of main memory at one moment, but become completely useless a few moments later. Therefore, each cost value is a snapshot over a window at a certain point in time with limited expressiveness for at most few periods ahead in the future. We define the general goal function for our tuning component: At a given point in time t with a configuration c, find a configuration c' that has less accumulated I/O costs over the next n periods. The optimal window size and the number of forecast periods again depend on the actual workload; slowly changing workloads enable more precise cost estimations for longer periods, while rapidly changing workloads also decrease accuracy of future costs.

For simplicity, our cost model only considers buffer service time, i.e., the time needed to handle a page fix request. Of course, costs assigned to a specific buffer are dominantly determined by the number of I/Os performed. On a buffer miss (denoted m), a victim page has to be selected for replacement and flushed, if necessary, before the requested page is fetched from disk. Accordingly, a buffer miss causes at least one read operation, but may also cause several writes for flushing write-ahead log and victim page. The ratio between

reads and synchronous writes is reflected by a weight factor f_{dirty}, which may vary over time and from buffer to buffer.

Depending on the characteristics of the underlying devices or blocking times under concurrent access, I/O times can also vary between various buffers. Hence, the costs of all buffers must be normalized to a common base to become comparable. We use here a second weight factor w_{buffer} for each buffer. As the time needed for a single I/O operation is easy to measure, these factors can be derived and adjusted at runtime causing low overhead. Finally, the cost of a buffer at the end of time period t is expressed as:

$$c_{buffer}(t) = w_{buffer}(t) \cdot (1 + f_{dirty}(t)) \cdot m(t)$$

Note, we assume that CPU costs can be safely ignored, either because they are independent of whether an operation can be performed on buffered data or requires additional I/O, or because additional CPU cycles for search routines in larger buffers are negligible compared to an I/O operation. In the remainder of this paper, we also assume that read and write operations have symmetric costs and a low variance. However, it should be evident that the presented basic model can be easily extended to take asymmetric read/write costs (e.g. for solid state drives), different costs for random and sequential I/O, and also the apportionment of preparatory, asynchronous flushes of dirty pages into account.

4.2 Decision Model

Our buffer balancing is based on the cost model of Section 4.1. In certain intervals, the buffer configuration is analyzed and optimized if main memory reallocations are promising reduced I/O costs for the entire system.

After each monitoring period, the buffer pools are ranked by their cost estimations as follows. The higher a buffer pool is ranked in the *save* list, the more costs can be saved (i.e., this equals to providing a higher benefit) by referring to the simulated buffer oversize. On the other hand, buffer pools are also ranked by their cost estimations for undersize figures, whereas the minimum cost increase is ranked top in the *rise* list. Using a greedy algorithm, buffer pool pairs are picked from the top of both lists as long as the cost reduction on the *save* list is higher than the increase on the *rise* list. Note, a buffer may occur in both lists, which typically indicates a "jump" and is thereby easily recognized. Finally, resize mechanisms are employed to perform the memory "shifts". The selected buffer from the *save* list is increased to allow more frames and references to be cached. A buffer chosen from the *rise* list, however, is shrunken, which may also include to flush victims to achieve a smaller buffer size. Note, an optimal solution is always achievable, but certainly requires more efforts. Therefore, we use greedy optimization because it is fast, cheap, and fairly good.

Oversize and undersize simulations for several buffer pools do not necessarily have the same size in bytes, which complicates memory shifts. However, fine-grained assignments may be required, which are also possible by extrapolating the buffer scaling figures between its real size and the simulated sizes.

To avoid thrashing, buffers chosen for resizing are removed from both ranking lists. The simulated undersize and oversize areas have to be adjusted as well, which is similar to the "regular" buffer resize. For instance, the number of hotset pages is reduced by selecting victims out of this subset and by switching their flags. Obviously, oversize areas can be kept or resized as desired.

Although resize decisions are sometimes heavy-weight operations (e.g., flushing pages), they only occur at the end of each monitoring period and are only performed as long as expected benefits justify them.

Period Refinements for Simulated Buffer Sizes

Accounting hit/miss numbers for multiple simulated and real buffer sizes over a certain period of time induces estimations errors. For instance, a smaller buffer causing more misses requires more time to process the same amount of buffer requests as the real one. On the other hand, a larger buffer having an improved hit ratio may require less time to process the requests, which are considered during this simulation and tuning period. Therefore, simulation-based cost accounting has to reuse the cost model's I/O weights for read and write operations to adjust the (simulation) periods. That means, undersize simulation has to limit I/O accounting as soon as the I/O budget that is physically possible is consumed and vice-versa for SBPX extensions.

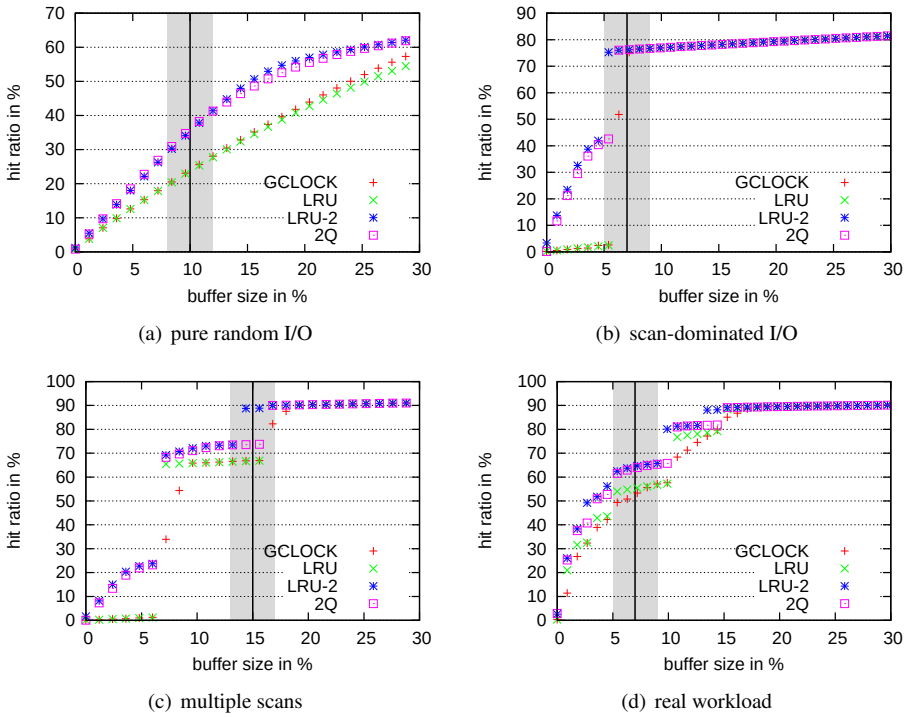
Switchable Propagation Algorithms

Adjusting memory assignments for buffer pools is also limited to the scalability prospects of a specific buffer algorithm. However, different buffer algorithms may perform differently and exchange of an algorithm would be an alternative tuning option without actually shifting memory. But different algorithms tend to use manifold figures such as access counters, timestamps, or history queues. The major problem is to carry over the current information when switching to a new algorithm. A poor alternative is to reset the entire propagation strategy. However, a practical way is to initialize the new algorithm by evicting all the "old" pages into the new algorithm and continue to use the new algorithm. The decision to switch the algorithm can only be based on a full simulation of an alternative propagation algorithm relying on a similar cost model as presented in Section 4.1.

5 Evaluation

Here, we want to evaluate the accuracy of our extensions as well as the decision quality for buffer balancing. But first, we have to describe our benchmark scenarios and their workloads.

As already stated in the introduction, buffers do not scale uniformly; thus, we generated reference strings for various (common) scenarios including random and sequential access of varying sizes.



(a) pure random I/O

(b) scan-dominated I/O

(c) multiple scans

(d) real workload

Figure 3: Buffer scalability for various workloads and replacement algorithms

5.1 Workload

In Figure 3(a)-3(d), we analyze the critical buffer size ranges for various access patterns whose characteristics are summarized in Table 1. Note, the total number of DB pages is equal to the first column's object size figure of each scenario in this table. The only uniformly scaling buffer is measured for workloads dominated by random I/O (see Figure 3(a)), where the overall hit ratio is – as expected – quite low. In this case, re-sizing extrapolations will work properly, but such an access behavior is unusual in databases. Dominating scans mixed with random access are modeled and measured in Figure 3(b). Although scan resistance is addressed by replacement algorithms, scan effects easily provoke "jumps" in the buffer performance. In such cases, the buffer hit rate dramatically increases as soon as often occurring scans entirely fit into the buffer. Such "jumps" remain undetected if monitoring happens only at one side of the "jump". The third workload shown in Figure 3(c) is a mixture of multiple scans and random accesses in a single buffer. This scenario may represent a more typical buffer usage pattern which exhibits a realistic buffer scaling. In Figure 3(c), several areas can be identified having different slopes, where each area boundary may cause uncertainty for extrapolations. In the last sample workload shown in Figure 3(d), a mixture of high-locality scans and some share of random accesses is analyzed. This typical workload scenario causes several (small) "jumps" resulting in a

Table 1: Workload characteristics

workload	Figure 3(a) (random)		Figure 3(b) (scan)		Figure 3(c) (jumps)		
request share in %	50	50	25	75	10	65	25
∑object size (pages)	150k	22k	150k	7k	150k	7k	13k
access type	rnd	rnd	rnd	seq	rnd	seq	seq

workload	Figure 3(d) (real)							
request share in %	10	10	10	20	10	20	10	10
∑object size (pages)	250k	5k	10k	10k	500	500	1k	2k
access type	rnd	rnd	seq	seq	seq	seq	seq	seq

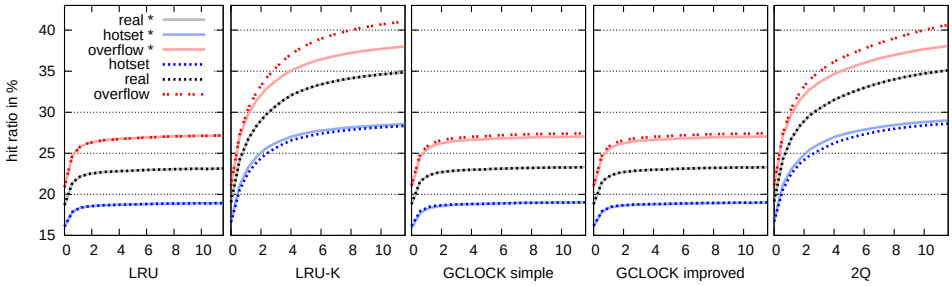


Figure 4: Estimation accuracy for workload *random* (buffer calls $\times 100.000$ on x-axis)

stair-case pattern. In this case, fine-grained extrapolations necessary for buffer tuning may quickly fail, although the slope in the average is quite similar.

We want to show in the subsequent sections that our algorithms are capable of identifying and handling all of these (more or less) typical workload scenarios.

5.2 Accuracy

The quality of buffer balancing is based on the estimation quality of our extended buffer algorithms. Therefore, we need to evaluate the estimation accuracy for the differing workloads. For the following experiments, the gray-shaded areas in Figures 3(a)–3(d) specify the simulated ranges centered around the actual buffer sizes indicated by the black lines. For simplicity, we always use a fixed range of ± 2 % of the total DB size. For each workload, we measure the undersize and oversize estimation accuracy. Each of the Figures 4–7 contains the results of five algorithms using the same workload and up to 1.2 Mio buffer calls. The lines marked with an asterisk (*) illustrate the simulation-based hit ratios and, to enable comparison, the others show those of real buffers having the same sizes.

The first graphs are always showing the standard LRU behavior, which is always delivering perfect estimation accuracy; however, its hit ratio performance is not the best. But its lightweight simulation is definitely a plus. In contrast, the LRU-K results (second graphs) constantly indicate top hit ratios but show weaknesses in forecast quality. Especially, the downsize simulation of the *scan* workload fails with a dramatic overestimation.

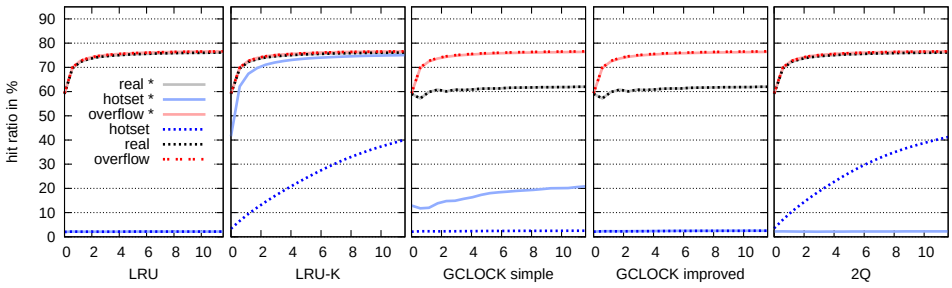


Figure 5: Estimation accuracy for workload *scan* (buffer calls $\times 100.000$ on x-axis)

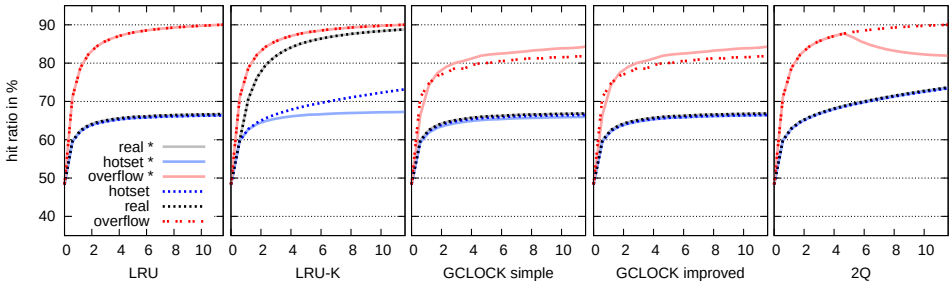


Figure 6: Estimation accuracy for workload *jumps* (buffer calls $\times 100.000$ on x-axis)

The results for GCLOCK in Figure 5 and 7 (third graphs) reveal its sensitivity to page order and clock-hand position for hotset simulations. By adding a second clock hand and forward pointers to simulate a separate clock for the hotset pages, we achieve considerably better accuracy (fourth graph), but its performance is always behind all other strategies.

On the right-hand side, we measure the forecast quality provided by the simplified 2Q algorithm. In all scenarios, it delivers top results while only requiring low maintenance overhead. However, forecast quality is disappointing in some scenarios. Similar to LRU-K, it fails for workload *scan*, but in the opposite direction with underestimation. Further, we observe a suddenly degrading forecast quality for the workloads *jumps* and *real*. Even worse, oversize estimations as well as undersize estimations are affected. Even the use of a separate policy for the oversize buffer does not lead to better results.

The experiments reveal that our simulations based on the locality principle lead to trustworthy estimations in many cases. On one side, simple algorithms like LRU and GCLOCK fit well into our framework. On the other side, more advanced algorithms such as LRU-K and 2Q also allow lightweight estimations, but suffer from unpredictable estimation errors in some scenarios. The reasons are built-in mechanisms to achieve scan-resistancy, which are hard to model in simulations. Further, these algorithms do not allow logical composition of individual buffers.

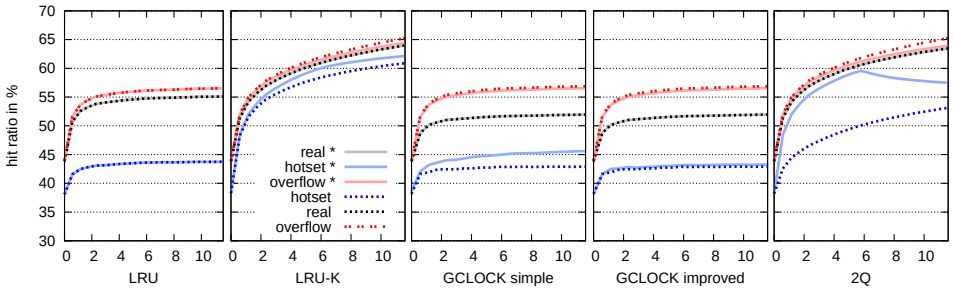


Figure 7: Estimation accuracy for workload *real* (buffer calls $\times 100.000$ on x-axis)

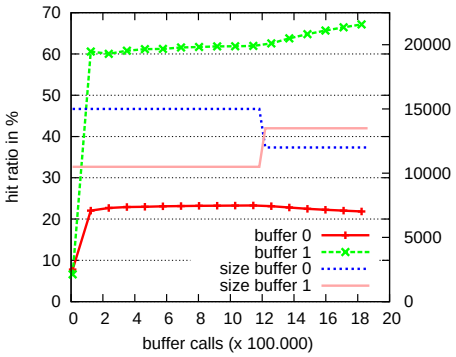


Figure 8: Buffer balancing *random* vs. *scan*

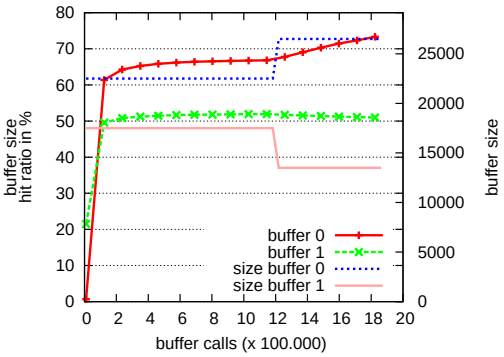


Figure 9: Buffer balancing *jump* vs. *real*

5.3 Buffer Balance

In Figure 8, the self-tuning mechanism presented in Section 4.2 automatically tunes two buffers, where buffer 0 was fed with *random* workload from Figure 3(a) and buffer 1 with *scans* shown in Figure 3(b). Buffer sizes (i.e., simulation and real) are chosen as described in Section 5.2. Due to space limitation, we present the results only for the improved GCLOCK and a fixed memory shift granularity of 2 % of the DB size. After the buffers were warmed up (i.e., after 1.2 Mio buffer calls), the cost model triggers all memory shifts. The *random* workload buffer was shrunken according to its hotset simulation, whereas buffer 1 was increased. Although the hit ratio of buffer 0 slightly descends, the overall I/O performance improves, because the hit ratio of buffer 1 increases considerably.

Because the self-tuning decisions are based on a cost model, they are applicable for arbitrary scenarios. In our second example, we again use two buffers, one that is fed from the *jumps* workload generator and the other from the *real* workload generator as shown in Figure 3(c) and Figure 3(d). In this setting, SBPX fails because its does not recognize that the size of buffer 0 is close to a "jump" boundary. However, as indicated by Figure 9, our downsizing simulation detects the pitfall and prevents buffer performance penalties.

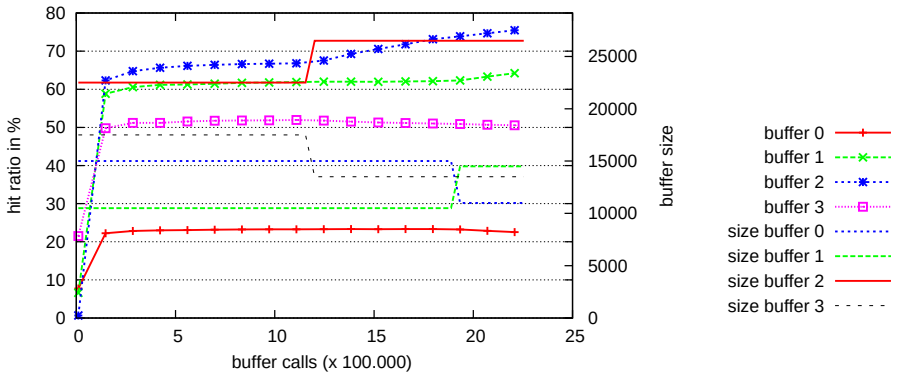


Figure 10: Balancing of four buffers under different workloads

Resizing two buffers is obviously simple. Therefore, we combine both experiments in a single setup shown in Figure 10. The cut-out shows two memory shifts leading to minor descends of the hit ratio on the one side but clear improvements on the other side resulting in a steadily improved buffer performance.

In summary, we could experimentally prove that buffer balancing can be achieved at low cost, but it heavily depends on accurate and lightweight forecasts for both directions – upsize and downsize.

6 Conclusions

Even after decades of research on buffer management and optimization, the problem of a reliable, dynamic adaptation of buffer memory allocation is not fully solved. In this work, we studied opportunities to forecast buffer resizing effects to support harm-free self-tuning decisions. As downsizing a buffer is accompanied with severe risks of thrashing, we argued that reliable prediction of downsizing effects is a key point for self-tuning decisions. Furthermore, we argued that additional overhead for these forecasts must not add noticeable overhead to normal processing. Therefore, we focused on lightweight techniques to exploit knowledge from the buffer replacement strategies for forecasts and presented possible solutions for four families of replacement algorithms.

In our experiments, we could show that forecast quality is heavily dependent on the actual strategy. It seems that sophisticated strategies like LRU-K and 2Q make it hard or even impossible to get reliable forecasts for either upsizing, downsizing, or both. We found that there are two reasons for this: First, such algorithms use history-recording techniques, which are very costly to emulate for varying sizes. Second, they are extremely sensible to configuration parameters, which cannot be easily negotiated between differing buffer sizes. However, simpler, yet widely-used strategies like LRU and GCLOCK turned out to allow for cheap and highly accurate or even perfect forecasts. In conjunction with a

simple cost model and a greedy algorithm, we demonstrated the use of forecasts to improve buffer hit ratios without the risk of severe performance penalties. Following the idea of differing "stages" in 2Q to improve buffer behavior, our findings suggest to think about further partitioning of buffers with complex replacement strategies into several distinct buffers with simpler but more predictable strategies. This way, forecasts would generally become reliable and fragmentations issues were automatically resolved by the self-tuning capabilities.

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