Automatic Heap Sizing: Taking Real Memory Into Account

Ting Yang Emery D. Berger Matthew H. Hertz Scott F. Kaplan[†] J. Eliot B. Moss
tingy@cs.umass.edu emery@cs.umass.edu hertz@cs.umass.edu sfkaplan@cs.amherst.edu moss@cs.umass.edu

Department of Computer Science
University of Massachusetts
Amherst, MA 01003

[†]Department of Computer Science
Amherst College
Amherst, MA 01002-5000

ABSTRACT

Heap size has a huge impact on the performance of garbage collected applications. A heap that barely meets the application's needs causes excessive GC overhead, while a heap that exceeds physical memory induces paging. Choosing the best heap size *a priori* is impossible in multiprogrammed environments, where physical memory allocations to processes change constantly. We present an automatic heap-sizing algorithm applicable to different garbage collectors with only modest changes. It relies on an analytical model and on detailed information from the virtual memory manager. The model characterizes the relation between collection algorithm, heap size, and footprint. The virtual memory manager tracks recent reference behavior, reporting the current footprint and allocation to the collector. The collector uses those values as inputs to its model to compute a heap size that maximizes throughput while minimizing paging. We show that our adaptive heap sizing algorithm can substantially reduce running time over fixed-sized heaps.

1. INTRODUCTION

Java and C# have made garbage collection (GC) much more widely used. GC provides many advantages, but it also carries a potential liability: paging, a problem known for decades. Early on, Barnett devised a simple model of the relationship between GC and paging [9]. One of his conclusions is that total performance depends on that of the swap device, thus showing that paging costs can dominate. An optimal policy is to control the size of the heap based on the amount of free memory. Moon [18] observed that when the heap accessed by GC is larger than real memory, the GC spends most of its time *thrashing*. Because disks are 5 to 6 orders of magnitude slower than RAM, even a little paging ruins performance. Thus we must hold in real memory essentially all of a process's pages—its *footprint*—to preserve performance.

The footprint of a GCed process is determined mostly by the *heap size*. A sufficiently small heap prevents paging during GC. However, an overly small heap causes more frequent GCs. Ideally, one chooses the *largest* heap size for which the *entire footprint is cached*. That size GCs often enough to keep the footprint from overflowing real memory, while minimizing time spent collecting.

Unfortunately, from a single process's viewpoint, available real memory is not constant. In a multiprogrammed environment, the operating system's virtual memory manager (VMM) dynamically allocates memory to each process and to the file system cache. Thus space allocated to one process changes over time in response to *memory pressure*–the demand for memory space exhibited by the workload. Even in systems with large main memories, large file system caches induce memory pressure. Disk accesses caused by paging or by misses in the file cache both hurt system performance.

Contributions: We present an automatic adaptive heap-sizing algorithm. Periodically, it obtains the current *real memory allocation* and *footprint* of the process from the VMM. It then adjusts the heap size so that the new footprint just fits in the allocation. It thus prevents paging during GC while minimizing time spent doing GC. To adjust heap size effectively, the heap sizing algorithm uses an analytical model of how changes to the specific collector's heap size affects its footprint. We have models for *semi-space* and *Appel* collectors, and we show that the models give reliable predictions.

We also present a design of a VMM that gathers the data necessary to calculate the footprint as needed by the model. This VMM tracks references only to less recently used ("cool") pages. It dynamically adjusts the number of recently used ("hot") pages, whose references it does not track, so that the total overhead falls below a threshold. This VMM gathers reference distribution information sufficient for our models while adding only 1% to running time.

In exchange for this 1%, our algorithm selects heap sizes on the fly, reducing GC time and nearly eliminating paging. It reduces total time by up to 90% (typically by 10–40%). Our simulation results show, for a variety of benchmarks, using both *semi-space* and *Appel* collectors, that our algorithm selects good heap sizes for widely varying real memory allocations. Thus far we have developed models only for non-incremental, stop-the-world, GC, but in future work hope to extend the approach to include incremental and concurrent collectors.

2. RELATED WORK

Heap size selection has received surprisingly little attention, despite its impact on performance. We discuss papers we know of, and then consider interfaces to VMMs.

Heap sizing: Kim and Hsu examine the paging behavior of GC for the SPECjvm98 benchmarks [17]. They run each program with various heap sizes on a system with 32MB of RAM. They find that performance suffers when the heap does not fit in real memory, and that when the heap is larger than real memory it is often better to grow the heap than to collect. They conclude that there is an optimal heap size for each program for a given real memory. We agree, but choosing optimal sizes *a priori* does not work in the context of multiprogramming: available real memory changes dynamically.

The work most similar to ours is by Alonso and Appel, who also exploit information from the VMM to adjust heap size [4]. Their GC periodically queries the VMM to find the current amount of available memory, and then adjusts heap size in response. Our work differs from theirs in several key respects. While their approach shrinks the heap when memory pressure is high, they do not expand heaps when pressure is low, which would reduce GC frequency. Further, they rely on standard interfaces to the VMM, which provide at best a coarse estimate of memory pressure. Our VMM algorithm captures detailed reference information, providing reliable estimates.

Brecht et al. adapt Alonso and Appel's approach to control heap growth. Rather than interact with the VMM, they offer ad hoc rules for two given memory sizes [12]. These sizes are *static*, so their technique works only if the application always has that specific amount of memory. Also, they use the Boehm-Weiser mark-sweep collector [11], which can grow its heap but cannot shrink it.

Cooper et al. dynamically adjust the heap size of an Appel style collector according to a given memory usage target [13]. If the target matches the amount of free memory, their approach adjusts the heap to make full use of it. Our work automatically identifies the target given data from the VMM. Furthermore, our model captures the relation between footprint and heap size, making our approach more general.

There are several existing systems that adjust heap size depending on the current environment. MMTk [10] and BEA JRockit [3] can, in response to the live data ratio or pause time, change their heap size using a set of pre-defined ratios. HotSpot [1] has the ability to adjust heap size with respect to pause time, throughput, and footprint limits given as command line arguments. Novell Netware Server 6 [2] polls the VMM every 10 seconds, and shortens its GC invocation interval to collect more frequently, when memory pressure is high. All of them rely on some pre-defined parameters or command line arguments to control the adjustment of heap size, which makes adaptation slow and inaccurate. Given our communication with the VMM and our analytical model, our algorithm selects good heap sizes quickly and gives precise control of application footprint.

Virtual Memory Interfaces: Systems typically offer a way for programs to communicate detailed information *to* the VMM, but expose very little in the other direction. Many UNIX and UNIX-like systems support the `madvise` system call, by which applications may offer information about their reference behavior to the VMM. We know of no systems that expose more detailed information about an application's virtual memory behavior beyond memory residency (which pages are "in core" (`mincore`)). Out interface is even simpler: the VMM gives the program two values: its *footprint* (how much memory the program needs to avoid significant paging), and its *allocation* (real memory available to it now). The GC uses these values to adjust heap size accordingly.

3. GC PAGING BEHAVIOR ANALYSIS

To build robust mechanisms for controlling paging behavior of GCed applications it is important first to understand those behaviors. Hence we studied those behaviors by analyzing memory reference traces for a set of benchmarks, executed under each of several collectors, for a number of heap sizes. The goal was to reveal, for each collector, the regularities in the reference patterns and the relation between heap size and footprint.

Methodology Overview: We used an instrumented version of Dynamic SimpleScalar (DSS) [14] to generate memory reference traces. We pre-processed these with the SAD reference trace reduction algorithm [15, 16]. (SAD stands for Safely Allowed Drop, which we explain below.) For a given *reduction memory size* of *m* pages, SAD produces a substantially smaller trace that triggers the same exact sequence of faults for a simulated memory of at least *m* pages, managed with least-recently-used (LRU) replacement. SAD drops most references that hit in memories smaller than *m*, keeping only the few necessary to ensure that the LRU stack order is the same for pages in stack positions *m* and beyond. We processed the SAD-reduced traces with an LRU stack simulator to obtain the number of faults for all memory sizes no smaller than *m* pages.

SAD and LRU Extensions: Because our garbage collectors make calls to `mmap` (to request demand-zero pages) and `munmap` (to free regions evacuated by GC), we needed to extend the SAD and LRU models to handle these primitives sensibly. Details are in Appendix A.

Application platform: We used as our Java platform Jikes RVM version 2.0.1 [6, 5] built for the PowerPC. We optimized the system images to the highest optimization level and included all normal run-time system components in the images, to avoid run-time compilation of those components. The most cost-effective mode for running Jikes RVM is with its *adaptive* compilation system. Because the adaptive system uses time-driven sampling to invoke optimization, it is non-deterministic. We desired comparable non-deterministic executions to make our experiments repeatable, so we took compilation logs from a number of runs of each benchmark in the adaptive system, determined the median optimization level for each method, and directed the system to compile each method to that method's median level as soon as the system loaded the method. We call this the *pseudo-adaptive* system, and it indeed achieves the goals of determinism and high similarity to typical adaptive system runs.

Collectors: We considered three collectors: mark-sweep (MS), semi-space copying collection (SS), and Appel-style generational copying collection (Appel) [7]. MS is one of the original "Watson" collectors written at IBM. It uses segregated free lists and separate spaces and GC triggers for small versus large objects (where "large" means more than 2KB). SS and Appel come from the Garbage Collector Toolkit (GCTk), developed at the University of Massachusetts Amherst and contributed to the Jikes RVM open source repository. They do not have a separate space for large objects. SS is a straightforward copying collector that triggers collection when a semi-space (half of the heap) fills, copying reachable objects to the other semi-space. Appel adds a nursery, where it allocates all new objects. Nursery collection copies survivors to the current old-generation semi-space. If the space remaining is too small, it then does an old-generation semi-space collection. In any case, the new nursery size is half the total heap size allowed, minus the space used in the old generation. Both SS and Appel allocate linearly in their allocation area.

Benchmarks: We use a representative selection of programs from SPECjvm98. We also use `ipsixql`, an XML database program, and `pseudojbb`, which is the SPECjbb2000 benchmark modified to perform a fixed number of iterations (thus making time and GC comparisons more meaningful). We ran all these on their "large" (size 100) inputs.

3.1 Results and Analysis

We consider the results for `jack` and `javac` under the SS collector. The results for the other benchmarks are strongly similar. (The full set of graphs of faults and estimated time for GC and mutator are available at http://www-ali.cs.umass.edu/t̃ingy/CRAMM/results/) Figure 1(a) and (d) show the number of page faults for varying real memory allocations. Each curve in each graph comes from one simulation of the benchmark in question, at a particular real memory allocation. Note that the vertical scales are *logarithmic*. Note that the final drop in each curve happens in order of increasing heap size, i.e., the smallest heap size drops to zero page faults at the smallest allocation.

We see that each curve has three regions. At the smallest memory sizes, we see extremely high paging. Curiously, larger *heap* sizes perform better for these small *memory* sizes! This happens because most of the paging occurs during GC, and a larger heap size causes fewer GCs, and thus less paging.

The second region of each curve is a broad, flat region representing substantial paging. For a range of real memory allocations, the program repeatedly allocates in the heap until the heap is full, and the collector then walks over most of the heap, copying reachable objects. Both steps are similar to looping over a large array, and require an allocation equal to a semi-space to avoid paging. (The separate graphs for faults during GC and faults during mutator execution support this conclusion.)

Finally, the third region of each curve is a sharp drop in faults that occurs once the allocation is large enough to capture the "looping" behavior. The final drop occurs at an allocation that is near to half the heap size plus a constant (about 30MB for `jack`). This regularity suggests that there is a base amount of memory needed for the Jikes RVM system and the application code, plus additional space for a semi-space of the heap.

We further see that, for most memory sizes, GC faults dominate mutator (application) faults, and that mutator faults have a component that depends on heap size. This dependence results from the mutator's allocation of objects in the heap between collections.

The behavior of MS strongly resembles the behavior of SS, as shown in Figure 1(b) and (e). The final drop in the curves tends to be at the heap size plus a constant, which is logical in that MS allocates to its heap size, and then collects. MS shows other plateaus, which we suspect have to do with there being some locality in each free list, but the paging experienced on even the lowest plateau gives a substantial increase in program running time. It is important to select a heap size whose final drop-off is contained by the current real memory allocation.

The curves for Appel (Figure 1)(c) and (f) are also more complex than those for SS, but show the same pattern of a final drop in page faulting at 1/2 the heap size plus a constant.

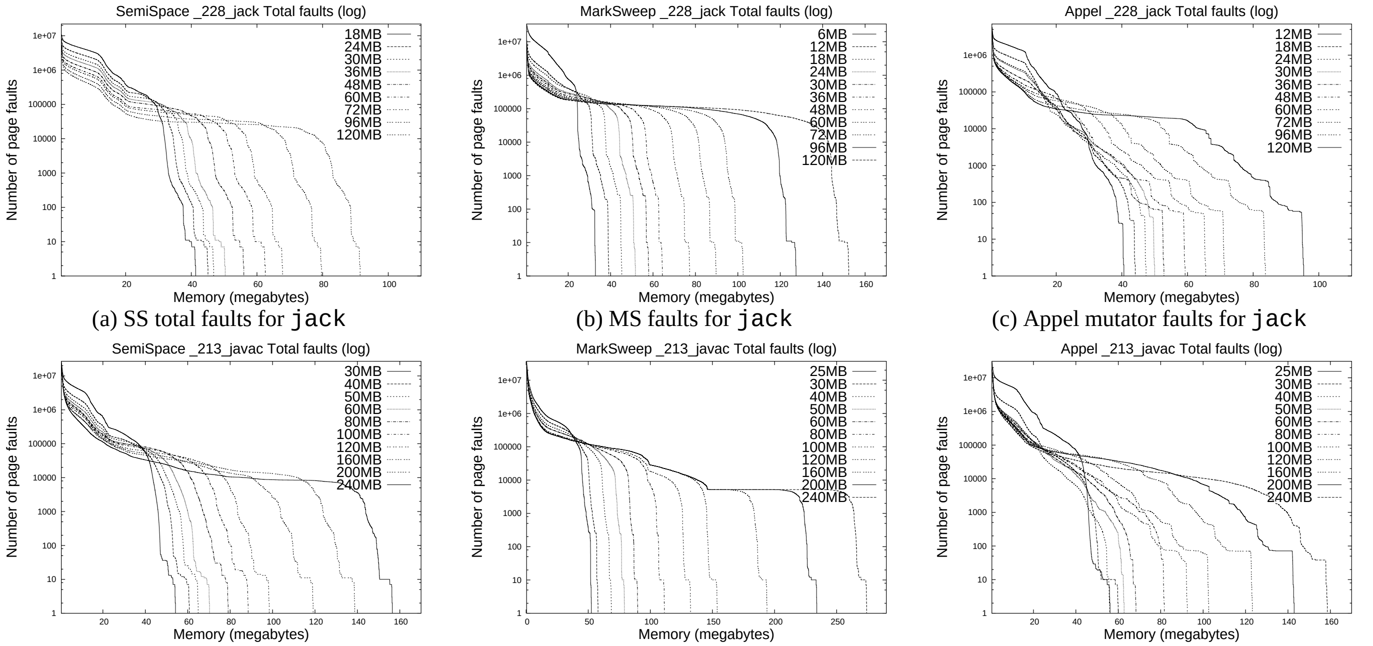
3.2 Proposed Heap Footprint Model

These results lead us to propose that the minimum real memory R required to run an application at heap size h without substantial paging is approximately $a \cdot h + b$, where a is a constant that depends on the GC algorithm (1 for MS and 0.5 for SS and Appel) and b depends partly on Jikes RVM and partly on the application itself. The intuition behind the formula is this: an application repeatedly fills its available heap ($1/2 \cdot h$ for Appel and SS; h for MS), and then, during a full heap collection, copies out of that heap the portion that is live (b).

In sum, we suggest that required real memory is a linear function of heap size. We tested this hypothesis using results derived from those already presented. In particular, suppose we choose a threshold value t, and we desire that the estimated paging cost not exceed t times the application's running time with no paging. For a given value of t, we can plot the minimum real memory allocation required for each of a range of heap sizes such that the paging overhead not exceed t.

Figure 2 shows, for `jack` and `javac` and the three collectors, plots of the real memory allocation necessary at varying heap sizes such that paging remains within a range of thresholds. What we see is that the linear model is excellent for MS and SS, and still good for Appel, across a large range of heap sizes and thresholds, and often not very sensitive to the threshold value. For Appel, beyond a certain heap size there are nursery collections but no full heap collections. At that heap size, there is a "jump" in the curve, but on each side of this heap size there are two distinct regimes that are both linear.

For some applications, our linear model does not hold

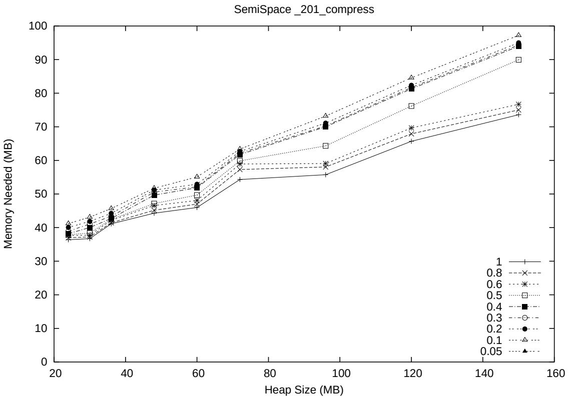


(a) SS total faults for `jack` (b) MS faults for `jack` (c) Appel mutator faults for `jack`

(d) SS total faults for `javac` (e) MS GC faults for `javac` (f) Appel mutator faults for `javac`

Figure 1: Paging: Faults according to memory size and heap size

as well. Figure 3 shows results for `ipsixql` under Appel. For smaller threshold values the linear relationship is still strong, modulo the shift from some full collections to none in Appel. While we note that larger threshold values ultimately give substantially larger departures from linearity, users are most likely to choose small values for *t* in an attempt nearly to eliminate paging. Only under extreme memory pressure would a larger value of *t* be desirable. The linear model appears to hold well enough for smaller *t* to consider using it to drive an adaptive heap-sizing mechanism.



(a) Memory needed for `ipsixql` under Appel

Figure 3: (Real) memory required to obtain given paging overhead

4. DESIGN AND IMPLEMENTATION

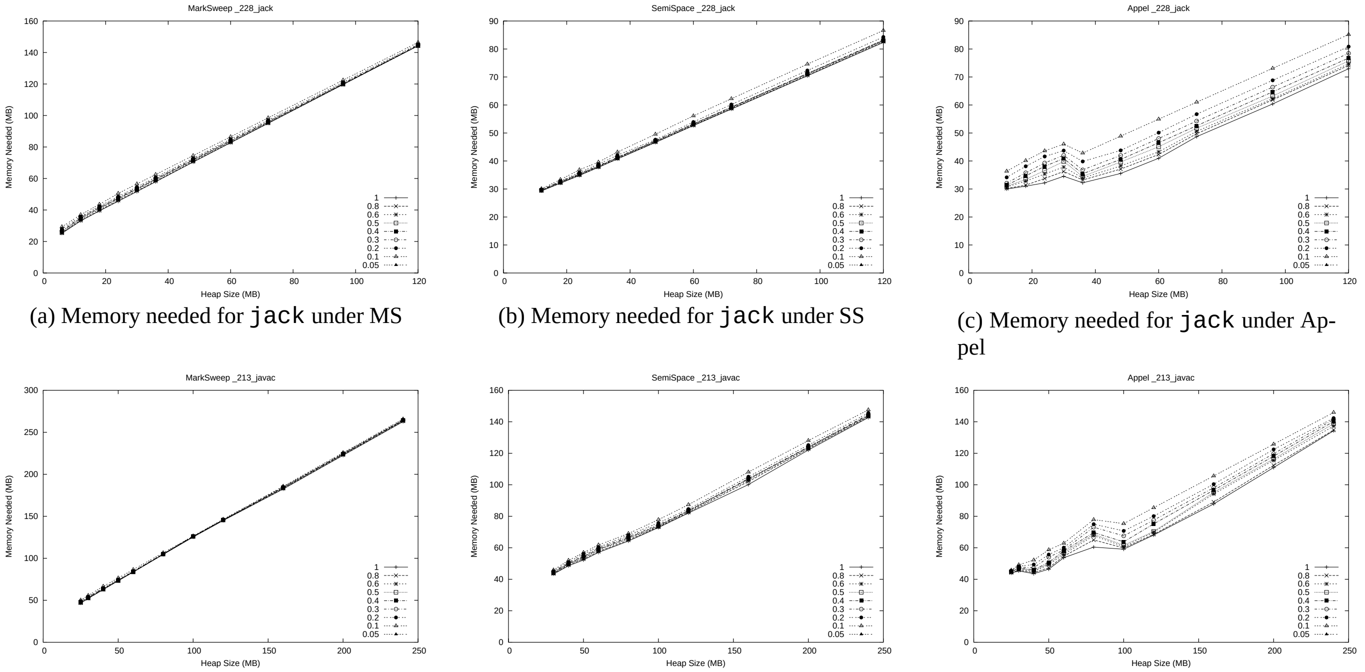
Given the footprint and allocation for a process, the model described in Section 3.2 can be used to select a good heap size. To implement this idea, we modified two garbage collectors as well as the underlying virtual memory manager (VMM). Specifically, we changed the VMM to collect information sufficient to calculate the footprint, and we changed the garbage collectors to adjust the heap size online. Furthermore, we altered the VMM to communicate to the collectors the information necessary to perform the heap size calculation.

We implemented the modified garbage collectors within the Jikes RVM [6, 5] Java system, which we ran on Dynamic SimpleScalar [14]. We used these same tools to generate the traces discussed in Section 3.2. In this case, we modified the portion of DSS that models an operating system's VMM to track and communicate the process footprint.

4.1 Emulating a Virtual Memory Manager

DSS is an instruction-level CPU simulator that emulates the execution of a process under PPC Linux. We enhanced its emulation of the VMM so that it more realistically modeled the operation of a real system. Since our algorithm relies on a VMM that conveys both the current allocation and the current footprint to the garbage collector, it is critical that the emulated VMM be sufficiently realistic to approximate the overhead that our methods would impose.

A low cost replacement policy: Our emulated VMM uses a SEGQ [8] structure to organize pages; that is, main memory is divided into two segments where the more recently used pages are placed in the first segment—a *hot set* of pages—while less recently used pages are in



(a) Memory needed for `jack` under MS

(b) Memory needed for `jack` under SS

(c) Memory needed for `jack` under Appel

(d) Memory needed for `javac` under MS

(e) Memory needed for `javac` under SS

(f) Memory needed for `javac` under Appel

Figure 2: (Real) memory required across range of heap sizes to obtain given paging overhead

the second segment—the *cold set*. When a new page is faulted into main memory, it is placed in the first (hot) segment. If that segment is full, one page is moved into the second segment. If the second segment is full, one page is evicted to disk, thus becoming part of the *evicted set*.

We use the CLOCK algorithm—a common, low-overhead algorithm that approximates LRU—for the hot set. This use of hardware reference bits allows pages to be moved into the cold set in an order that is close to true LRU order. Our model maintains 8 reference bits. As the CLOCK passes a particular page, we shift its byte of reference bits left by one position and *or* the hardware *referenced* bit into the low position of the byte. The rightmost *one* bit of the reference bits determines the relative age of the page. When we need to evict a hot set page to the cold set, we choose the page of oldest age that comes first after the current CLOCK pointer location.

We apply page protection to pages in the cold set, and store the pages in order of their eviction from the hot set. If the program references a page in the cold set, the VMM restores the page's permissions and moves it to the hot set, potentially forcing some other page out of the hot set and into the cold set. Thus, the cold set behaves like a normal LRU queue.

We modified DSS to emulate both hardware reference bits and protected pages. Our emulated VMM uses these capabilities to implement our CLOCK/LRU SEGQ policy. For a given main memory size, it records the number of minor page faults on protected pages and the number of major page faults on non-resident pages. We can later ascribe service times for minor and major fault handling and thus determine the running time spent in the VMM.

Handling unmapping: As was the case for the SAD and LRU algorithms, our VMM emulation needs to deal with unmapping of pages. The cold and evicted sets work essentially as one large LRU queue, so we handle unmapped pages for those portions as we did for the LRU stack algorithm. As for the hot set, suppose an unmap operation causes k pages to be unmapped in the hot set. Our strategy is to shrink the hot set by k pages and put k place holders at the head of the cold set. We then allow future faults from the cold or evicted set to grow the hot set back to its target size.

4.2 Virtual Memory Footprint Calculations

Existing real VMMs lack capabilities critical for supporting our heap sizing algorithm. Specifically, they do not gather sufficient information to calculate the footprint of a process, and they lack a sufficient interface for interacting with our modified garbage collectors. We describe the modifications required to a VMM—modifications that we applied to our emulated VMM—to add these capabilities.

We have modified our VMM to measure the current footprint of a process, where the *footprint* is defined as the *smallest allocation whose page faulting will increase the total running time by more than a fraction t over the non-paging running time*.[1] When $t = 0$, the correspond-

[1] *Footprint* has sometimes been used to mean the total number of

ing allocation may be wasting space to cache pages that receive very little use. When t is small but non-zero, the corresponding allocation may be substantially smaller in comparison, and yet still yield only trivial amounts of paging, so we think non-zero thresholds lead to a more useful definition of *footprint*.

LRU histograms: To calculate this footprint, the VMM records an *LRU histogram* [19, 20]. For each reference to a page found at position i of the LRU queue for that process, we increment a count $H[i]$. This histogram allows the VMM to calculate the number of page faults that would occur with each possible allocation to the process. The VMM finds the footprint by finding the allocation size where the number of faults is just below the number that would cause the running time to exceed the threshold t.

Maintaining a true LRU queue would impose too much overhead in a real VMM. Instead, our VMM uses the SEGQ structure described in Section 4.1 that approximates LRU at low cost. Under SEGQ, we maintain histogram counts only for references to pages in the cold and evicted sets. Such references incur a minor or major fault, respectively, and thus give the VMM an opportunity to increment the appropriate histogram entry. Since the hot set is much smaller than the footprint, the missing histogram information on the hot set does not harm the footprint calculation.

In order to avoid large space overheads, we group queue positions and their histogram entries together into *bins*. Specifically, we use one bin for each 64 pages (256KB given our page size of 4KB). This granularity is fine enough to provide a sufficiently accurate footprint measurement while reducing the space overhead substantially.

Mutator vs. collector referencing: The mutator and garbage collector exhibit drastically different reference behaviors. Furthermore, when the heap size is changed, the reference pattern of the garbage collector itself will change, while the reference pattern of the mutator will likely remain similar (although slightly different thanks to objects that may have moved during collection).

Therefore, the VMM relies on notification from the garbage collector when collection begins and when it ends. One histogram records the mutator's reference pattern, and another histogram records the collector's. When the heap size changes, we clear the collector's histogram, since the previous histogram data no longer provides a meaningful projection of future memory needs.

When the VMM calculates the footprint of a process, it combines the counts from both histograms, thus incorporating the page faulting behavior of both phases.

Unmapping pages: A garbage collector may elect to *unmap* a virtual page, thereby removing it from use. As we discussed previously, we use place holders to model unmapped pages. They are crucial not only in determining the correct number of page faults for each memory size, but also in maintaining the histograms correctly, since the histograms indicate the number of faults one would experience at various memory sizes.

Histogram decay: Programs exhibit *phase behavior*: during a phase, the reference pattern is constant, but when one phase ends and another begins, the reference pattern may change dramatically. Therefore, the histograms must reflect the referencing behavior from the current phase. During a phase, the histogram should continue to accumulate. When a phase change occurs, the old histogram values should be decayed rapidly so that the new reference pattern will emerge.

Therefore, the VMM periodically applies an *exponential decay* to the histogram. Specifically, it multiplies each histogram entry by a decay factor $\alpha = \frac{63}{64}$, ensuring that older histogram data has diminishing influence on the footprint calculation. Previous research has shown that the decay factor is not a sensitive parameter when using LRU histograms to guide adaptive caching strategies [19, 20].

To ensure that the VMM applies decay more rapidly in response to a phase change, we must identify when phase changes occur. Phases are *memory size relative*: a phase change for a hardware cache is not a phase change for a main memory. Therefore, the VMM must respond to referencing behavior near the main memory allocation for the process. Rapid referencing of pages that substantially affect page replacement for the current allocation indicate that a phase change relative to that allocation size is occurring [19, 20].

The VMM therefore maintains a *virtual memory clock* (this is quite distinct from, and should not be confused with the clock of the CLOCK algorithm). A reference to a page in the evicted set advances the clock by 1 unit. A reference to a page in the cold set, whose position in the SEGQ system is i, advances the clock by $f(i)$. If the hot set contains h pages, and the cold set contains c pages, then $h < i \leq h + c$ and $f(i) = \frac{i-h}{c}$.[2] The contribution of the reference to the clock's advancement increases linearly from 0 to 1 as the position nears the end of the cold set, thus causing references to pages that are near to eviction to advance the clock more rapidly.

Once the VMM clock advances $\frac{M}{16}$ units for an M-page allocation, the VMM decays the histogram. The larger the memory, the longer the decay period, since one must reference a larger number of previously cold or evicted pages to constitute a phase change.

Hot set size management: A typical VMM uses a large hot set to avoid minor faults. The cold set is used as a "last chance" for pages to be re-referenced before being evicted to disk. In our case, though, we want to maximize the useful information (LRU histogram) that we collect, so we want the hot set to be as *small* as possible, without causing undue overhead from minor faults. We thus set a target *minor fault overhead*, stated as a fraction of application running time, say 1% (a typical value we used).

unique pages used by a process, and sometimes the memory size at which no page faulting occurs. Our definition is taken from this second meaning. We choose not to refer to it as a *working set* because that term has a larger number of poorly defined meanings.

[2] If the cold set is large, the high frequency of references at lower queue positions may advance the clock too rapidly. Therefore, for a total allocation of M pages, we define $c' = max(c, \frac{M}{2})$, $h' = min(h, \frac{M}{2})$, and $f(i) = \frac{i-h'}{c'}$.

Periodically (described below) we consider the overhead in the recent past. We calculate this as the (simulated) time spent on minor faults since the last time we checked, divided by the total time since the last time we checked. For "time" we use the number of instructions simulated, and assume an approximate execution rate of 10^9 instructions/sec. We charge 2000 instructions (equivalent to 2μs) per minor fault. If the overhead exceeds 1.5%, we increase the hot set size; if it is less than 0.5%, we decrease it (details in a moment). This simple adaptive mechanism worked quite well to keep the overhead within bounds, and the 1% value provided information good enough for the rest of our mechanisms to work.

How do we add or remove pages from the hot set? Our technique for growing the hot set by k pages is to move into the hot set the k hottest pages of the cold set. To shrink the hot set to a target size, we run the CLOCK algorithm to evict pages from the hot set, but *without* updating the reference bits used by the CLOCK algorithm. In this way the oldest pages in the hot set (insofar as reference bits can tell us age) end up at the head of cold set, with the most recently used nearer the front (i.e., in proper age order).

How do we trigger consideration of hot set size adjustment? To determine when to grow the hot set, we count what we call *hot set ticks*. We associate a weight with each LRU queue entry from positions $h+1$ through $h+c$, such that each position has weight $w = (h+c+1-i)/c$. Thus, position $h+1$ has weight 1 and $h+c+1$ has weight 0. For each minor fault that hits in the cold set, we increment the hot set tick count by the weight of the position of the fault. When the tick count exceeds 1/4 the size of the hot set (representing somewhat more than 25% turnover of the hot set), we trigger a size adjustment test. Note that the chosen weighting counts faults near the hot set boundary more than ones far from it. If we have a high overhead that we can fix with reasonable hot set growth, we will find it more quickly; conversely, if we have many faults from the cold end of the cold set, we may be encountering a phase change in the application and should be careful not to adjust the hot set size too eagerly.

To handle the case where we should consider shrinking the hot set, we consider the passage of (simulated) real time. If, when we handle a fault, we find that we have not considered an adjustment within τ seconds, we trigger consideration. We use a value of 16×10^6 instructions, corresponding to $\tau = 16$ms.

When we want to grow the hot set, how do we compute a new size? Using the current overhead, we determine the number of faults by which we exceeded our target overhead since the last time we considered adjusting the hot set size. We multiply this times the average hot-tick weight of minor faults since that time, namely *hot ticks / minor faults*; we call the resulting number N:

$$W = \mathit{hot\ ticks}/\mathit{minor\ faults}$$

$$\mathit{target\ faults} = (\Delta t \times 1\%)/2000$$

$$N = W \times (\mathit{actual\ faults} - \mathit{target\ faults})$$

Multiplying by the factor W avoids adjusting too eagerly. Using recent histogram counts for pages at the hot end of the cold set, we add pages to the hot set until we have added ones that account for N minor faults since the last time we considered adjusting the hot set size.

When we want to shrink the hot set, how do we compute a new size? In this case, we do not have histogram information, so we assume that (for changes that are not too big) the number of minor faults changes linearly with the number of pages removed from the hot set. Specifically, we compute a desired fractional change:

$$\mathit{fraction} = (\mathit{target\ faults} - \mathit{actual\ faults})/\mathit{target\ faults}$$

Then, to be conservative, we reduce the hot set size by only 20% of this fraction:

$$\mathit{reduction} = \mathit{hot\ set\ size} \times \mathit{fraction} \times .20$$

We found this scheme to work very well in practice.

VMM/GC interface: The GC and VMM communicate with system calls. The GC initiates communication at the beginning and ending of each collection. When the VMM receives a system call marking the beginning of a collection, it switches from the mutator to the collector histogram. It returns no information to the GC at that time.

When the VMM receives a system call for the ending of a collection, it performs a number of tasks. First, it calculates the footprint of the process based on the histograms and the threshold t for page faulting. Second, it determines the current main memory allocation to the process. Third, it switches from the collector to the mutator histogram. Finally, it returns to the GC the footprint and allocation values. The GC may use these values to calculate a new heap size such that its footprint will fit into its allocated space.

4.3 Adjusting Heap Size

In Section 3 we described the virtual memory behavior of the MS, SS, and Appel collectors in Jikes RVM. We now describe how we modified the SS and Appel collectors so that they modify their heap size in response to available real memory and the application's measured footprint. (Note that MS, unless augmented with compaction, cannot readily shrink its heap, so we did not modify it and drop it from further consideration.) We consider first the case where Jikes RVM starts with the heap size requested on the command line, and then adjusts the heap size after each GC in response to the current footprint and available memory. This gives us a scheme that at least potentially can adapt to changes in available memory during a run. Next, we augment this scheme with a startup adjustment, taking into account from the beginning of a run how much memory is available at the start. We describe this mechanism for the Appel collector, and at the end describe the (much simpler) version for SS.

Basic adjustment scheme: We adjust the heap size after each GC, so as to derive a new nursery size. First, there are several cases in which we do *not* try to adjust the heap size:

- When we just finished a nursery GC that is triggering a full GC. We wait to adjust until after the full GC.

- On startup, i.e., before there are any GCs. (We describe later our special handling of startup.)
- If the GC was a nursery GC, and the nursery was "small", meaning less than 1/2 of the maximum amount we can allocate (i.e., less than 1/4 of the current total heap size). Footprints from small nursery collections tend to be misleadingly small. We call this constant the *nursery filter factor*, which controls which nursery collections heap size adjustment should ignore.

Supposing none of these cases pertain, we then act a little differently after nursery versus full GCs. After a nursery GC, we first compute the survival rate of the just completed GC (bytes copied divided by size of from-space). If this survival rate is greater than any survival rate we have yet seen, we estimate the footprint of the *next* full GC:

$$eff = current\ footprint + 2 \times survival\ rate \times old\ space\ size$$

where the *old space size* is the size *before* this nursery GC.[3] We call this footprint the *estimated future footprint*, or *eff* for short. If the *eff* is less than available memory, we make no adjustment. The point of this calculation is to prevent over-eager growing of the heap after nursery GCs. Nursery GC footprints tend to be smaller than full GC footprints; hence our caution about using them to grow the heap.

If the *eff* is more than available memory, or if we just performed a full heap GC, we adjust the heap size, as we now describe. Our first step is to estimate the slope of the footprint versus heap size curve (corresponding to the slope of the lines in Figure 2. In general, we use the footprint and heap size of the two most recent GCs to determine this slope. However, after the first GC we have only one point, so in that case we assume a slope of 2 (for $\Delta heap\ size/\Delta footprint$). Further, if we are considering *growing* the heap, we multiply the slope by 1/2, to be conservative. We call this constant the *conservative factor* and use it to control how conservatively we should grow the heap. In Section 5, we provide a sensitivity analysis for the *conservative* and *nursery filter factors*.

Using simple algebra, we compute the *target heap size* from the slope, current and old footprint, and old heap size. ("Old" means after the previous GC; "current" means after the current GC.):

$$old\ size + slope \times (current\ footprint - old\ footprint)$$

Startup heap size: We found that the heap size adjustment algorithm we gave above work well much of the time, but has difficulty if the initial heap size (given by the user on the Jikes RVM command line) is larger than the footprint. The underlying problem is that the first GC causes a lot of paging, yet we do not adjust the heap size until after that GC. Hence we added a startup adjustment. From the currently available memory (a value supplied by the VMM on request), we compute an acceptable initial heap size:

$$Min(initial\ heap\ size\ , 2 \times (available - 20\text{MB}))$$

Heap size adjustment for SS: SS in fact uses the same adjustment *algorithm* as Appel. The critical difference is that in SS there are no nursery GCs, only full GCs.

5. EXPERIMENTAL EVALUATION

To test our algorithm we ran each benchmark described in Section 3 using the range of heap sizes used in Section 3.2 and a selection of fixed main memory allocation sizes. We used each combination of these parameters with both the standard garbage collectors (which use a static heap size) and our dynamic heap-sizing collectors. We chose the real memory allocations to reveal the effect of using large heaps in small allocations as well as small heaps in large allocations. In particular, we sought to evaluate the ability of our algorithm to grow *and* to shrink the heap, and to compare its performance to the static heap collectors in both cases.

We compare the performance of the collectors by measuring their estimated running time, derived from the number of instructions simulated. We simply charge a fixed number of instructions for each page fault to estimate total execution time. We further assume that writing back dirty pages can be done asynchronously so as to interfere minimally with application execution and paging. We ignore other operating system costs, such as application I/O requests. These modeling assumptions are reasonable because we are interested primarily in order-of-magnitude comparative performance estimates, not in precise absolute time estimates. The specific values we used assume that a processor achieves an average throughput of 1×10^9 instructions/sec and that a page fault stalls the application for 5ms $= 5 \times 10^6$ instructions. We attribute 2,000 instructions to each soft page fault, i.e 2μs, as mentioned in Section 4.2. For our adaptive semi-space collector, we use the threshold $t = 5\%$ for computing the footprint. For our adaptive Appel collector we use $t = 10\%$. (Appel completes in rather less time overall and since there are a number of essentially unavoidable page faults at the end of a run, 5% was unrealistic for Appel.)

5.1 Adaptive vs. Static Semi-space

Figure 4 shows the estimated running time of each benchmark for varying initial heap sizes under the SS collector. We see that for nearly every combination of benchmark and initial heap size, our adaptive collector changes to a heap size that performs at least as well as the static collector. The left-most side of each curve shows initial heap sizes and corresponding footprints that do not consume the entire allocation. The static collector under-utilizes the available memory and performs frequent collections, hurting performance. Our adaptive collector grows the heap size to reduce the number of collections without incurring paging. At the smallest initial heap sizes, this adjustment reduces the running time by as much as 70%.

At slightly larger initial heap sizes, the static collector performs fewer collections as it better utilizes the available memory. On each plot, we see that there is an initial

[3] The factor $2 \times$ *survival rate* is intended to estimate the volume of old space data referenced and copied. It is optimistic about how densely packed the survivors are in from-space. A more conservative value for the factor would be $1 +$ *survival rate*.

heap size that is ideal for the given benchmark and allocation. Here, the static collector performs well, while our adaptive collector often matches the static collector, but sometimes increases the running time a bit. Only pseudojbb and _209_db experience this maladaptivity. We believe that fine tuning our adaptive algorithm will likely eliminate these few cases.

When the initial heap size becomes slightly larger than the ideal, the static collector's performance worsens dramatically. This initial heap size yields a footprint that is slightly too large for the allocation. The resultant paging for the static allocator has a huge impact, slowing execution under the static allocator 5 to 10 fold. Meanwhile, the adaptive collector shrinks the heap size so that the allocation completely captures the footprint. By performing slightly more frequent collections, the adaptive collector consumes a modest amount of CPU time to avoid a significant amount of paging, thus reducing the running time by as much as 90%.

When the initial heap size grows even larger, the performance of the adaptive collector remains constant. However, the running time with the static collector decreases gradually. Since the heap size is larger, it performs fewer collections, and it is those collections and their poor reference locality that cause the excessive paging. Curiously, if a static collector is going to use a heap size that causes paging, it is better off using an excessively large heap size!

Observe that for these larger initial heap sizes, even the adaptive allocator cannot match the performance achieved with the ideal heap size. This is because the adaptive collector's initial heap sizing mechanism cannot make a perfect prediction, and the collector does not adjust to a better heap size until after the first full collection.

A detailed breakdown: Table 1 provides a breakdown of the running time shown in one of the graphs from Figure 4. Specifically, it provides the results for the adaptive and static semi-space collectors for varying initial heap sizes with _213_javac. It indicates, from left to right: the number of instructions executed (billions); the number of minor and major faults; the number of collections; the percentage of time spent handling minor faults; the number of major faults that occur within the first two collections with the adaptive collector; the number of collections before the adaptive collector learns ("warms-up") sufficiently to find its final heap size; the percentage of improvement in terms of estimated time.

We see that at small initial heap sizes, the adaptive collector adjusts the heap size to reduce the number of collections, and thus the number of instructions executed, without incurring paging. At large initial heap sizes, the adaptive mechanism dramatically reduces the major page faults. Our algorithm found its target heap size within two collections, and nearly all of the paging occurred during that "warm-up" time. Finally, it controlled the minor fault cost well, approaching but never exceeding 1%.

5.2 Adaptive vs. Static Appel

Figure 5 shows the estimated running time of each benchmark for varying initial heap sizes under the Appel collector. The results are qualitatively similar to those for the adaptive and static semi-space collectors. For all of the benchmarks, the adaptive collector yields significantly improved performance for large initial heap sizes that cause heavy paging with the static collector. It reduces running time by as much as 90%.

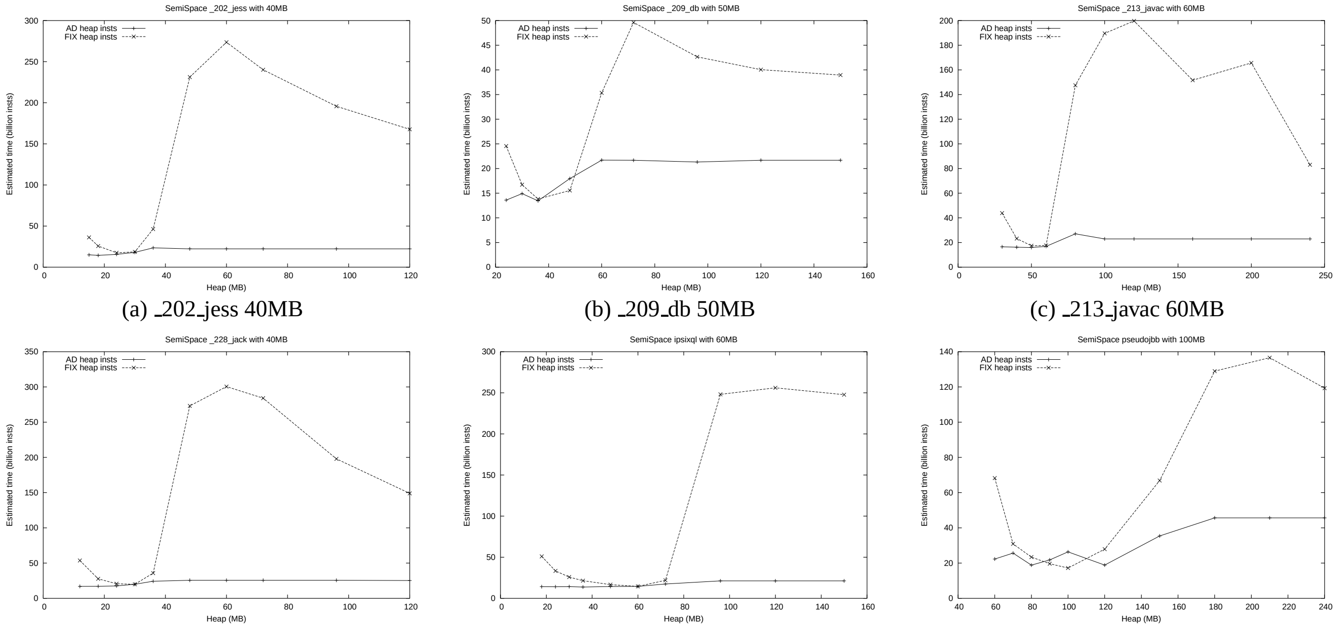
For about half of the benchmarks, the adaptive collector improves performance almost as dramatically for small initial heap sizes. However, for the other benchmarks, there is little or no improvement. The Appel algorithm uses frequent nursery collections, and less frequent full heap collections. For our shorter-lived benchmarks, the Appel collector incurs only 1 or 2 full heap collections. Therefore, by the time that the adaptive collector selects a better heap size, the execution ends.

Furthermore, our algorithm is more likely to be maladaptive when its only information is from nursery collections. Consider _228_jack at an initial heap size of 36MB. That heap size is sufficiently small that the static collector incurs no full heap collections. For the adaptive collector, the first several nursery collections create a footprint that is larger than the allocation, so the collector reduces the heap size. This heap size is small enough to force the collector to perform a full heap collection that references far more data than the nursery collections did. Therefore, the footprint suddenly grows far beyond the allocation and incurs heavy paging. The nursery collection leads the adaptive mechanism to predict an unrealistically small footprint for the select heap size.

Although the adaptive collector then chooses a much better heap size following the full heap collection, execution terminates before the system can realize any benefit. In general, processes with particularly short running times may incur the costs of having the adaptive mechanism find a good heap size, but not reap the benefits that follow. Unfortunately, most of these benchmarks have short running times that trigger only 1 or 2 full heap collections with pseudo-adaptive builds.

Parameter sensitivity: It is important, when adapting the heap size of an Appel collector, to filter out the misleading information produced during small nursery collections. Furthermore, because a maladaptive choice to grow the heap too aggressively may yield a large footprint and thus heavy paging, it is important to grow the heap conservatively. The algorithm described in Section 4.3 employs two parameters: the *conservative factor*, which controls how conservatively we grow the heap in response to changes in footprint or allocation, and the *nursery filter factor*, which controls which nursery collections to ignore.

We carried out a sensitivity test on these parameters. We tested all combinations of conservative factor values of $\{0.66, 0.50, 0.40\}$ and nursery filter factor values of $\{0.25, 0.5, 0.75\}$. Figure 6 shows _213_javac under the adaptive Appel collector for all nine combinations of these parameter values. Many of the data points in this plot overlap. Specifically, varying the conservative factor has no effect on the results. For the nursery filter factor, values of 0.25 and 0.5 yield identical results, while 0.75 produces slightly improved running times at middling to large initial heap sizes. The effect of these parameters



(a) _202_jess 40MB (b) _209_db 50MB (c) _213_javac 60MB

(d) _228_jack 40MB (e) ipsixql 60MB (f) pseudojbb 100MB

Figure 4: The estimated running time for the static and adaptive SS collectors for all benchmarks over a range of initial heap sizes.

Heap	Inst's ($\times 10^9$)		Minor faults		Major faults		GCs		Minor fault cost		MF	W	Ratio
(MB)	AD	FIX	AD	FIX	AD	FIX	AD	FIX	AD	FIX	2GC		AD/FIX
30	15.068	42.660	210,611	591,028	207	0	15	62	0.95%	0.95%	0	2	62.28%
40	15.251	22.554	212,058	306,989	106	0	15	28	0.95%	0.93%	0	1	30.04%
50	14.965	16.860	208,477	231,658	110	8	15	18	0.95%	0.94%	0	1	8.22%
60	14.716	13.811	198,337	191,458	350	689	14	13	0.92%	0.94%	11	1	4.49%
80	14.894	12.153	210,641	173,742	2,343	27,007	14	9	0.96%	0.97%	2236	1	81.80%
100	13.901	10.931	191,547	145,901	1,720	35,676	13	7	0.94%	0.90%	1612	2	88.92%
120	13.901	9.733	191,547	128,118	1,720	37,941	13	5	0.94%	0.89%	1612	2	88.63%
160	13.901	8.540	191,547	111,533	1,720	28,573	13	3	0.94%	0.88%	1612	2	85.02%
200	13.901	8.525	191,547	115,086	1,720	31,387	13	3	0.94%	0.91%	1612	2	86.29%
240	13.901	7.651	191,547	98,952	1,720	15,041	13	2	0.94%	0.87%	1612	2	72.64%

Table 1: A detailed breakdown of the events and timings for _213_javac under the static and adaptive SS collector over a range of initial heap sizes. *Warm-up* is the time, measured in the number of garbage collections, that the adaptivity mechanism required to select its final heap size.

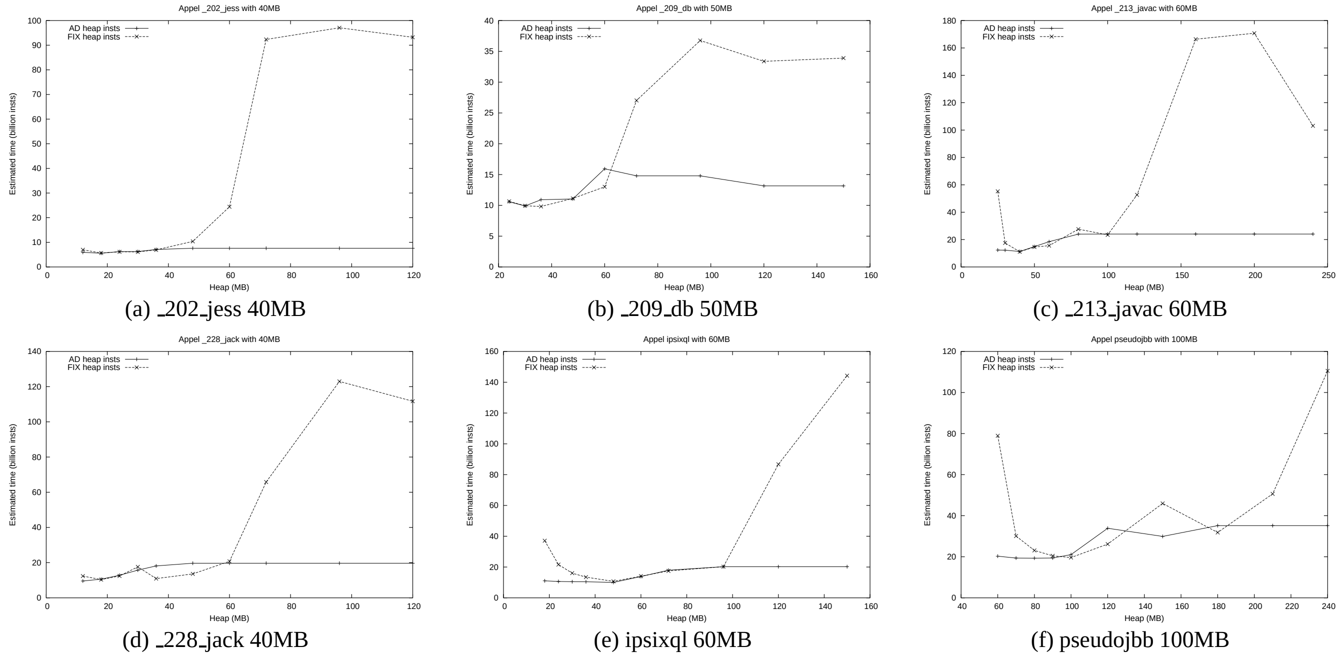
is dominated by the performance improvement that the adaptivity provides over the static collector.

Dynamically changing allocations: The results presented so far show the performance of each collector for an unchanging allocation of real memory. Although the adaptive mechanism finds a good, final heap size within two full heap collections, it is important that the adaptive mechanism also quickly adjust to dynamic changes in allocation that occur mid-execution.

Figure 7 shows the result of running _213_javac with the static and adaptive Appel collectors using varying initial heap sizes. Each plot shows results both from a static 60MB allocation and a dynamically changing allocation that begins at 60MB. The left-hand plot shows the results of increasing that allocation to 75MB after 2 billion instructions (2 sec), and the right-hand plot shows the results of shrinking to 45MB after the same length of time.

When the allocation grows, the static collector benefits from the reduced page faulting that occurs at sufficient large initial heap sizes. However, the adaptive collector matches or improves on that performance. Furthermore, the adaptive collector is able to increase its heap size in response to the increased allocation, and reduce the garbage collection overhead suffered when the allocation does not increase.

The qualitative results for a shrinking allocation are similar. The static collector's performance suffers due to the paging caused by the reduced allocation. The adaptive



(a) _202_jess 40MB

(b) _209_db 50MB

(c) _213_javac 60MB

(d) _228_jack 40MB

(e) ipsixql 60MB

(f) pseudojbb 100MB

Figure 5: The estimated running time for the static and adaptive Appel collectors for all benchmarks over a range of initial heap sizes.

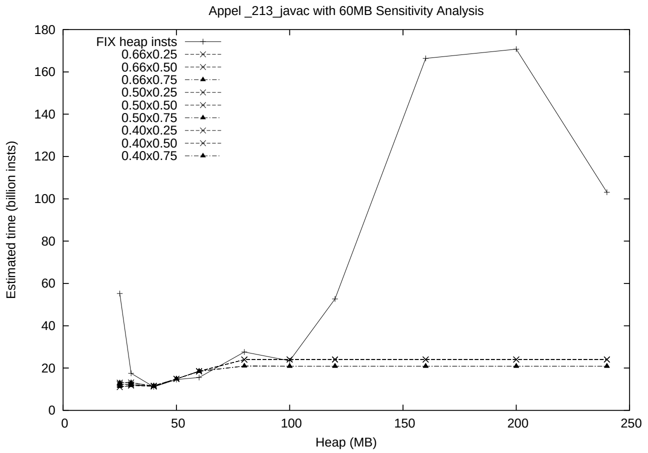


Figure 6: _213_javac under the Appel collectors given a 60MB initial heap size. We tested the adaptive collector with 9 different combinations of parameter settings, where the first number of each combination is the *conservative factor* and the second number is the *nursery filter factor*. The adaptive collector is not sensitive to the conservative factor, and is minimally sensitive to the nursery filter factor.

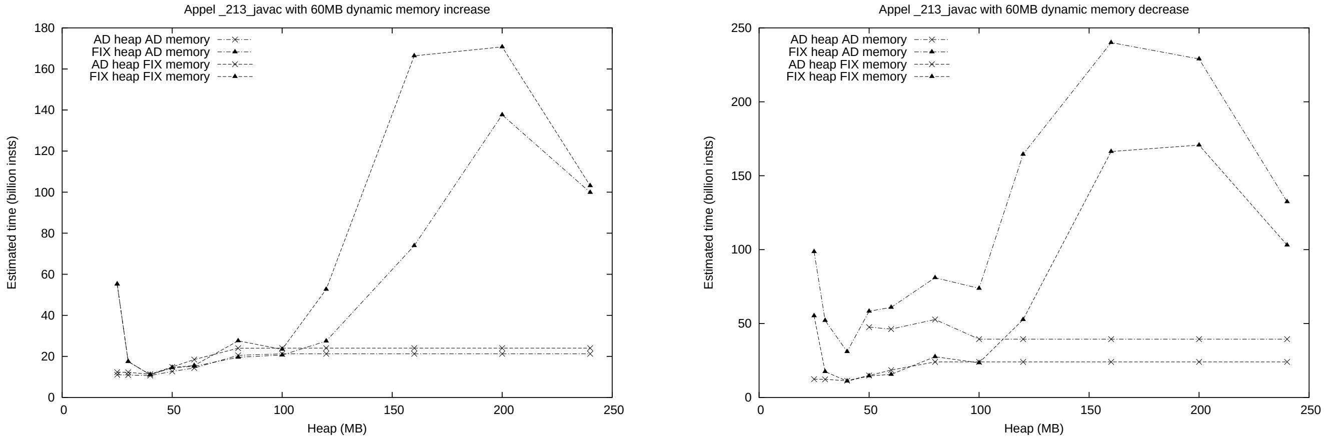
collector's performance suffers much less from the reduced allocation. When the allocation shrinks, the adaptive collector will experience page faulting during the next collection, after which it selects a new, smaller heap size at which it will collect more often.

Notice that when the allocation changes dynamically, the adaptive allocator dominates the static collector—there is no initial heap size at which the static collector matches the performance of the adaptive allocator. Under changing allocations, adaptivity is necessary to avoid excessive collection or paging.

We also observe that there are no results for the adaptive collector for initial heap sizes smaller than 50MB. When the allocation shrinks to 45MB, paging always occurs. The adaptive mechanism responds by shrinking its heap. Unfortunately, it selects a heap size that is smaller than the minimum required to execute the process, and the process ends up aborting. This problem results from the failure of our linear model, described in Section 3.2, to correlate heap sizes and footprints reliably at such small heap sizes. We believe we can readily address this problem in future work (possibly in the final version of this paper). Since our collectors can already change heap size, we believe that a simple mechanism can grow the heap rather than allowing the process to abort. Such a mechanism will make our collectors even more robust.

6. FUTURE WORK

Our adaptive collectors demonstrate the substantial performance benefits possible with dynamic heap resizing. However, this work only begins exploration in this direction. We are bringing our adaptive mechanism to other garbage collection algorithms such as mark-sweep. We seek to improve the algorithm to avoid the few cases in which it is maladaptive. Finally, we are modifying the Linux kernel to provide the VMM support described in Section 4.2 so that we may test the adaptive collectors on



(a) _213_javac 60MB− >75MB

(b) _213_javac 60MB− >45MB

Figure 7: Results of running _213_javac under the adaptive Appel collector over a range of initial heap sizes and *dynamically varying* real memory allocations. During execution, we increase (left-hand plot) or decrease (right-hand plot) the allocation by 15MB after 2 billion instructions.

a real system.

Other research is exploring a more fine-grained approach to controlling the paging behavior of garbage collectors. Specifically, the collector assists the VMM with page replacement decisions, and the collector explicitly avoids performing collection on pages that have been evicted to disk. We consider this approach to be orthogonal and complementary to adaptive heap sizing. We are exploring the synthesis of these two approaches to controlling GC paging.

Finally, we are developing new strategies for the VMM to select allocations for each process. A process that uses adaptive heap sizing presents the VMM with greater flexibility in trading CPU cycles for space consumption. By developing a model of the CPU time required for garbage collection at each possible allocation (and thus heap size), the VMM can choose allocations intelligently for processes that can flexibly change their footprint in response. When main memory is in great demand, most workloads suffer from such heavy paging that the system becomes useless. We believe that garbage collected processes whose heap sizes can adapt will allow the system to handle heavy memory pressure more gracefully.

7. CONCLUSION

Garbage collectors are sensitive to heap size and main memory allocation. We present a dynamic adaptive heap sizing algorithm. We apply it to two collectors, semi-space and Appel, requiring only minimal changes to the underlying collection algorithm to support heap size adjustments. For static allocations, our adaptive collectors match or improve upon the performance provided by the standard, static collectors in the vast majority of cases. The reductions in running time are often tens of percent, and as much as 90%. For initial heap sizes that are too large, we drastically reduce paging, and for initial heap sizes that are too small, we avoid excessive garbage collection.

In the presence of dynamically changing allocations, our adaptive collectors strictly dominate the static collectors. Since no one heap size will provide ideal performance when allocations change, adaptivity is necessary, and our adaptive algorithm finds good heap sizes within 1 or 2 full heap collections.

8. ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under grant number CCR-0085792. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF. We are also grateful to IBM Research for making the Jikes RVM system available under open source terms, and likewise to all those who developed SimpleScalar and Dynamic SimpleScalar and made them similarly available.

9. REFERENCES

[1] J2SE 1.5.0 Documentation - Garbage Collector Ergonomics. Available at http://java.sun.com/j2se/1.5.0/docs/guide/vm/gc-ergonomics.html.

[2] Novell Documentation: NetWare 6 - Optimizing Garbage Collection. Available at http://www.novell.com/documentation/index.html.

[3] Technical white paper - BEA weblogic jrockit: Java for the enterprise. http://www.bea.com/content/news_events /white_papers/BEA_JRockit_wp.pdf.

[4] R. Alonso and A. W. Appel. An advisor for flexible working sets. In *Proceedings of the 1990 SIGMETRICS Conference on Measurement and Modeling of Computer Systems*, pages 153–162, Boulder, CO, May 1990.

[5] B. Alpern, C. R. Attanasio, J. J. Barton, M. G. Burke, P. Cheng, J.-D. Choi, A. Cocchi, S. J. Fink, D. Grove, M. Hind, S. F. Hummel, D. Lieber,

V. Litvinov, M. F. Mergen, T. Ngo, V. Sarkar, M. J. Serrano, J. C. Shepherd, S. E. Smith, V. C. Sreedhar, H. Srinivasan, and J. Whaley. The Jalepeño virtual machine. *IBM Systems Journal*, 39(1), Feb. 2000.

[6] B. Alpern, C. R. Attanasio, J. J. Barton, A. Cocchi, S. F. Hummel, D. Lieber, T. Ngo, M. Mergen, J. C. Shepherd, and S. Smith. Implementing Jalepeño in Java. In *Proceedings of SIGPLAN 1999 Conference on Object-Oriented Programming, Languages, & Applications*, volume 34(10) of *ACM SIGPLAN Notices*, pages 314–324, Denver, CO, Oct. 1999. ACM Press.

[7] A. Appel. Simple generational garbage collection and fast allocation. *Software: Practice and Experience*, 19(2):171–183, Feb. 1989.

[8] O. Babaoglu and D. Ferrari. Two-level replacement decisions in paging stores. *IEEE Transactions on Computers*, C-32(12):1151–1159, Dec. 1983.

[9] J. A. Barnett. Garbage collection versus swapping. *Operating Systems Review*, 13(3), 1979.

[10] S. M. Blackburn, P. Cheng, and K. S. McKinley. Oil and Water? High Performance Garbage Collection in Java with MMTk. In *ICSE 2004, 26th International Conference on Software Engineering*, page to appear, May 2004.

[11] H.-J. Boehm and M. Weiser. Garbage collection in an uncooperative environment. *Software: Practice and Experience*, 18(9):807–820, Sept. 1988.

[12] T. Brecht, E. Arjomandi, C. Li, and H. Pham. Controlling garbage collection and heap growth to reduce the execution time of Java applications. In *Proceedings of the 2001 ACM SIGPLAN Conference on Object-Oriented Programming, Systems, Languages & Applications*, pages 353–366, Tampa, FL, June 2001.

[13] E. Cooper, S. Nettles, and I. Subramanian. Improving the performance of SML garbage collection using application-specific virtual memory management. In *Conference Record of the 1992 ACM Symposium on Lisp and Functional Programming*, pages 43–52, San Francisco, CA, June 1992.

[14] X. Huang, J. E. B. Moss, K. S. Mckinley, S. Blackburn, and D. Burger. Dynamic SimpleScalar: Simulating Java Virtual Machines. Technical Report TR-03-03, University of Texas at Austin, Feb. 2003.

[15] S. F. Kaplan, Y. Smaragdakis, and P. R. Wilson. Trace reduction for virtual memory simulations. In *Proceedings of the ACM SIGMETRICS 1999 International Conference on Measurement and Modeling of Computer Systems*, pages 47–58, 1999.

[16] S. F. Kaplan, Y. Smaragdakis, and P. R. Wilson. Flexible reference trace reduction for VM simulations. *ACM Transactions on Modeling and Computer Simulation (TOMACS)*, 13(1):1–38, Jan. 2003.

[17] K.-S. Kim and Y. Hsu. Memory system behavior of Java programs: Methodology and analysis. In *Proceedings of the ACM SIGMETRICS 2002 International Conference on Measurement and Modeling of Computer Systems*, volume 28(1), pages 264–274, Santa Clara, CA, June 2000.

[18] D. A. Moon. Garbage collection in a large LISP system. In *Conference Record of the 1984 ACM Symposium on Lisp and Functional Programming*, pages 235–245, 1984.

[19] Y. Smaragdakis, S. F. Kaplan, and P. R. Wilson. The EELRU adaptive replacement algorithm. *Performance Evaluation*, 53(2):93–123, July 2003.

[20] P. R. Wilson, S. F. Kaplan, and Y. Smaragdakis. The case for compressed caching in virtual memory systems. In *Proceedings of The 1999 USENIX Annual Technical Conference*, pages 101–116, Monterey, California, June 1999. USENIX Association.

APPENDIX

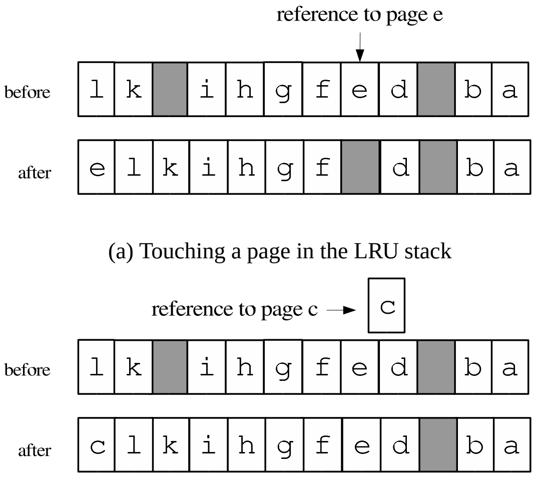
A. SAD AND LRU EXTENSIONS

As previously mentioned, we needed to extend the SAD and LRU models to handle `mmap` and `munmap` sensibly. Since SAD and LRU both treat the first access to a page not previously seen as a compulsory miss, `mmap` actually requires no special handling. We *do* need to handle `munmap` events specially, however. First we describe how to model unmapping for the LRU stack algorithm, and then describe how to extend SAD accordingly. Consider the diagram in Figure 8(a). The upper configuration shows the state of the stack after the sequence of references `a`, `b`, `c`, `d`, `e`, `f`, `g`, `h`, `i`, `j`, `k`, `l`, followed by unmapping `c` and `j`.

Note that we leave *place holders* in the LRU stack for the unmapped pages. Suppose the next reference is to page `e`. We bring `e` to the front of the stack, and move the first unmapped page place holder to where `e` was in the stack. Why is this correct? For memories of size 2 or less, it reflects the page-in of `e` and the eviction of `k`. For memories of size 3 through 7, it reflects the need to page in `e`, and that, because there is a free page, there is no need to evict a page. For memories of size 8 or more, it reflects that there will be no page-in or eviction. Note that if the next reference had been to `k` or `l`, we would not move any place holder, and if the next reference had been to `a`, the place holder between `k` and `i` would move down to the position of `a`. When a place holder reaches the old end of the stack (the right as we have drawn it), it may be dropped.

Now consider Figure 8(b), which shows what happens when we reference page `c`, a page *not* in the LRU stack (a compulsory miss or demand-zero page). We push `c` onto the front of the stack, and slide the previously topmost elements to the right, until we consume one place holder (or we reach the end of the stack). This is correct because it requires a page-in for all memory sizes, but requires eviction only for memories of size less than 3, since the third slot is free.

One might be concerned that the place holders can cause the LRU stack structure to grow without bound. However,



(a) Touching a page in the LRU stack

(b) Touching a page not in the LRU stack

Figure 8: LRU Stack Handling of Unmapped Pages

because of the way compulsory misses are handled (Figure 8(b)), the stack will never contain more elements than the maximum number of pages mapped at one time.

To explain the modifications to SAD, we first provide a more detailed overview of its operation. Given a reduction memory size *m*, SAD maintains an *m*-page LRU stack as well as a window of references from the reference trace being reduced. Critically, this window contains references only to those pages that are currently in the *m*-page LRU stack. Adding the next reference from the source trace to the front of this window triggers one of two cases. *Case one:* the reference does not cause eviction from the LRU stack (i.e., the stack is not full or the reference is to a page in the stack): we add the reference to the window, and, if the window contains *two* previous references to the same page, we delete the *middle* reference.*Case two:* the reference causes an eviction from the LRU stack: If *p* is the evicted page, then SAD removes references from the back of the window, emitting them to the reduced trace file, until no references to *p* remain in the window. This step preserves the window's property of containing references only to pages that are in the LRU stack. At the end of the program run, SAD flushes the remaining contents of the window to the reduced trace file.

An unmapped page affects SAD only if it is one of the *m* most recently used pages. If this case occurs, it is adequate to update the LRU stack by dropping the unmapped page and sliding other pages towards the more recently used end of the stack to close up the gap. Since that unmapped page no longer exists in the LRU stack, references to it must be removed from the window. Our modified SAD handles this case as it would an evicted page, emitting references from the back of the window until it contains no more references to the unmapped page. This also maintains SAD's guarantee that the window never holds more than $2m+1$ entries.