

Optimal Heap Limits for Reducing Browser Memory Use

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Garbage-collected language runtimes carefully tune heap limits to reduce garbage collection time and memory usage. However, there's a trade-off: a lower heap limit reduces memory use but increases garbage collection time. Classic methods for setting heap limits include manually tuned heap limits and multiple-of-live-size rules of thumb, but it is not clear when one rule is better than another or how to compare them.

We address this problem with a new framework where heap limits are set for multiple heaps at once. Our key insight is that every heap limit rule induces a particular allocation of memory across multiple processes, and this allocation can be sub-optimal. We use our framework to derive an optimal “square-root” heap limit rule, which minimizes total memory usage for any amount of total garbage collection time. Paradoxically, the square-root heap limit rule achieves this coordination without communication: it allocates memory optimally across multiple heaps without requiring any communication between those heaps.

To demonstrate that this heap limit rule is effective, we prototype it for V8, the JavaScript runtime used in Google Chrome, Microsoft Edge, and other browsers, as well as in server-side frameworks like node.js and Deno. On real-world web pages, our prototype achieves reductions of approximately 16.0% of memory usage while keeping garbage collection time constant. On memory-intensive benchmarks, reductions of up to 30.0% of garbage collection time are possible with no change in total memory usage.

CCS Concepts: • **Software and its engineering** → **Runtime environments**; • **Information systems** → **Browsers**.

Additional Key Words and Phrases: garbage collection, memory management, heap limit, JavaScript, web browser

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1 INTRODUCTION

Many modern programming languages are garbage-collected [Jones et al. 2012], freeing the programmer from manually managing memory. Achieving good performance in a garbage-collected language, however, requires controlling how often garbage collection occurs and how long it takes. Typically, garbage-collected language runtimes control garbage collection frequency by setting a limit on total memory usage (“heap size”) and collecting garbage once that limit is hit.¹

¹In production garbage-collected runtimes such as V8 or the JVM, there are lots of other triggers for garbage collection. Nevertheless, the heap limit does play a central role.

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Choosing a heap limit is a classic space-time trade-off. Set the heap limit too low, and the garbage collector will fire too often, slowing the program unacceptably. Set it too high, and the program consumes too much memory, interfering with other processes. In high-performance deployments of garbage-collected systems, setting heap memory limits manually to achieve the optimal trade-off is common [Shang 2020]. However, in dynamic environments this manual tuning is untenable. For example, web browsers start and stop applications frequently as their usually-inexpert users (i.e., your grandmother) browse the web; browsers must therefore set heap limits automatically, without relying on user expertise.

Heap limits affect memory usage, and memory usage is important to end users—perhaps even to you, dear reader. Memory usage is one of the most common complaints about web browsers [Vij 2022], with hundreds of articles instructing users on how to reduce their browser’s memory usage, with suggestions like uninstalling extensions, disabling security features, and deleting old user data [Vij 2022]. Major browser developers make significant efforts to reduce memory usage, such as Firefox’s “Are we Slim Yet” effort [Mozilla 2020] and Chrome’s “V8 Lite” effort [Alle et al. 2019]. And because the JavaScript heap is typically a large percentage of overall browser memory usage, often more than half, choosing appropriate heap limits is central to lowering browser memory use. This is all the more important on low-memory devices such as phones. On these devices, lower heap limits can allow more tabs to stay resident in memory, which not only makes browsing more convenient, but is also necessary to complete multi-tab workflows such as some single sign-on systems. Users of such devices cannot simply buy more memory, and even if they could, they may not have the money.

The challenge with deciding heap limits automatically is that it’s unclear what to optimize for. A typical approach is to set heap limits to some multiple of the live size [Hertz and Berger 2005]. But since there is a trade-off between memory usage and program run time, it’s not clear in what sense this rule of thumb is optimal or sub-optimal, or even how to compare it to some other approach. That said, there’s good reason to think that this rule is *not* optimal. State of the art garbage-collected language runtimes extend it with ad-hoc fixes, such as detecting when a program is idle and scheduling extra garbage collections [Degenbaev et al. 2016], capping/flooring the heap limit, or targeting a percentage of total run time. These ad-hoc fixes themselves conflict in complex ways, such as a idle collections conflicting with a run time target or run time targets conflicting with heap limit caps.

We introduce a new framework in which heap limit rules can be compared, based on the insight that heap limit rules not only affect the performance of a single program, but also the allocation of memory *across* programs. In our framework, a shared pool of memory must be split across multiple garbage-collected programs to minimize the total time spent in garbage collection. Optimal heap limit rules for multiple heaps must allocate available memory amongst the heaps in a way that minimizes total garbage collection time. We find that standard heap limit rules are *not* optimal, no matter how they are tuned. Therefore, running multiple garbage-collected programs using standard heap limit rules—opening multiple tabs in a web browser, for example—will use more memory and spend more time collecting garbage than necessary. Figure 1 shows the process graphically:² non-optimal heap limit rules misallocate memory between processes and thus do not achieve a pareto-optimal trade-off between memory usage and garbage collection time.

Luckily, our framework is analytically solvable, producing a “square-root” heap limit rule that *is* optimal in our framework. This means that multiple processes that each use identically-tuned square-root heap limit rules allocate memory amongst themselves so as to minimize total garbage

²Using synthetic data where garbage collection time is inversely proportional to heap memory usage, plus a horizontal/vertical offset.

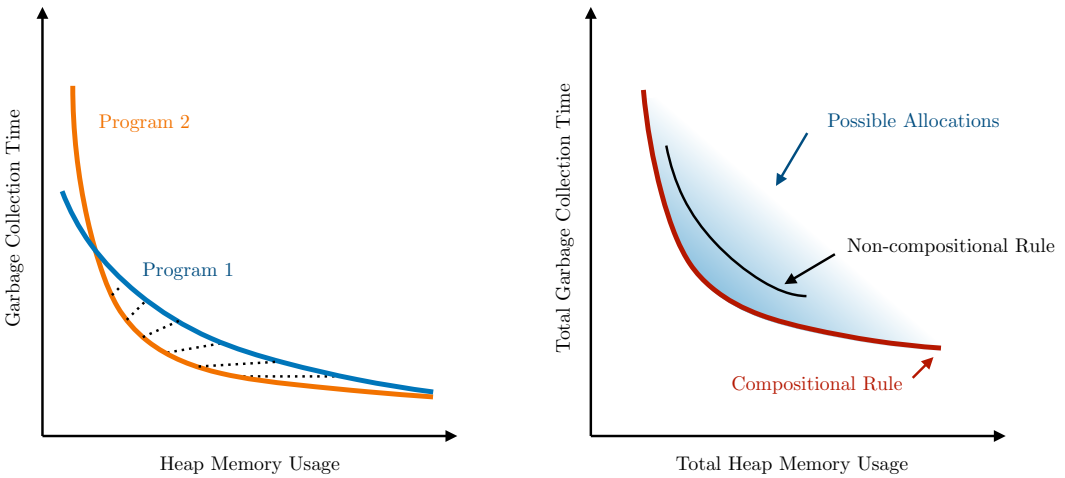


Fig. 1. Synthetic data showing the difference between compositional and non-compositional heap limit rules. In the left-hand plot, the garbage collection time and heap memory usage for two different programs is shown for varying heap limits. In the right-hand plot, both programs are run simultaneously and total heap memory usage and total garbage collection time across both programs is measured. Depending on the heap limit chosen for each program, any point in the blue region is achievable. The dotted lines in the left-hand plot and the black curve in the right-hand plot represent the behavior of a non-compositional heap limit rule as some tuning parameter is varied. This heap limit rule is not at the pareto frontier (as shown on the right-hand plot) because non-compositional heap limit rules mis-allocate memory among the programs. This means that, no matter how the parameter is tuned, the optimal trade-off between heap memory usage and garbage collection time cannot be achieved with this heap limit rule. A compositional heap limit rule, by contrast, allocates memory across programs in a pareto-optimal way, shown by the red curve.

collection time. Surprisingly, this does not require any communication between the processes, achieving a form of coordination without communication: each process sets its heap limit based on its observations of its own execution, without communicating any data with other processes, yet the resulting allocation of memory across processes nonetheless achieves the globally-minimal total garbage collection time. The lack of communication is especially attractive in an untrusted environment, like a web browser, since no communication means no side channels that could compromise the web's strong security properties. We call the combination of optimality in our framework and coordination without communication a **compositional** heap limit rule, because multiple such programs can be composed without manually tuning the heap limits of each.

We implement our square-root heap limit rule in V8, the state-of-the-art garbage-collected JavaScript runtime that powers Google Chrome, Microsoft Edge, and other browsers, as well as server-side frameworks such as node.js and Deno. V8's current heap limit computation is based around a core multiple-of-live-size rule that is modified, overridden, or adjusted by multiple heuristics, triggers, and asynchronous processes. In its place, our prototype, MemBalancer, monitors allocations in real time and adjusts heap limits on the fly using a single, uniform implementation of the square-root heap limit rule.

We evaluate MemBalancer on six real-world web applications: Facebook, Gmail, Twitter, CNN, Fox News, and ESPN. MemBalancer achieves a better trade-off between average heap usage and garbage collection time than V8's current heap limit rule. Depending on how MemBalancer is

tuned, an average reduction of 16.0% of average heap usage or 49.0% of total garbage collection time is achievable. On memory-intensive JavaScript benchmarks from the ACDC [Aigner et al. 2014] benchmark suite, MemBalancer demonstrates reductions of up to 8.2% of average heap usage without increasing total garbage collection time, or 30.0% of total garbage collection time without increasing average heap usage.

In summary, this paper contributes:

- The concept of a compositional heap limit rule, based on a framework that allocates a pool of memory across several garbage-collected programs (Section 4);
- A compositional “square-root” heap limit rule, which achieves coordination without communication and is optimal in our framework (Section 5);
- A prototype, named MemBalancer, of the compositional square-root heap limit rule for the V8 JavaScript engine (Section 6).

We evaluate our prototype on standard JavaScript benchmarks in Section 7.1 and on real-world websites in Section 7.2.

2 CASE STUDY

To understand why compositional heap limit rules reduce memory usage and garbage collection time, let’s examine the behavior of a compositional heap limit rule on three benchmarks from the JetStream 2 Javascript benchmark suite:³ Typescript, which runs the Typescript compiler on a fixed Typescript codebase; PDF.js, which renders a fixed PDF file with the PDF.js rendering engine; and Splay, which creates a splay tree and does a sequence of insert and delete operations on it. All three benchmarks run a kernel in a hot loop, making it easy to understand their garbage collection behavior. Notably, the PDF.js benchmark contains a memory leak, meaning that it consumes more and more memory over time.⁴ This memory leak causes increasing mis-allocation between the three benchmarks as the iteration count increases.⁵

Figure 2 illustrates the memory allocation behavior of two runs of this benchmark, one using V8’s current heap limit rule, and one using MemBalancer, our implementation of a compositional heap limit rule for V8. In each plot, the different colors represent different benchmarks, showing their memory use over time. The MemBalancer run uses 3.5% less memory, yet spends 20% less time garbage-collecting. This is because V8’s current heap limit rule is not compositional: it overallocates memory to some benchmarks and underallocates memory to others. Specifically, it allocates minimal memory to the Splay and TypeScript benchmarks, causing rapid garbage collections, while PDF.js is allowed a much larger heap. At its core, this is because V8’s current heap limit rule allocates memory proportionally to current live memory. Due to the memory leak, PDF.js has a large amount of live memory, and is thus allocated a large heap, even though it doesn’t use this heap particularly effectively. In the right plot, MemBalancer allocates less memory to PDF.js and more to Splay, dramatically reducing overall garbage collection time without much affecting overall memory use, due to its use of a compositional heap limit rule. Allocating slightly more memory to Splay and much less to PDF.js saves more than enough garbage collection time on Splay to compensate for extra garbage collection time on PDF.js.

To underscore this point, Table 1 contains point-in-time estimates of each thread’s live memory (L), allocation rate (g), and garbage collection speed (s) for the three benchmarks (captured from the MemBalancer run). The Splay benchmark is unusual in both allocating memory and collecting garbage much faster than Typescript or PDF.js. This suggests that Splay should receive much more

³These three benchmarks are the most memory-intensive of the 64 total JetStream benchmarks.

⁴To our knowledge this was first pointed out by Barrett et al. [2017].

⁵Sadly, memory leaks are also common in real-world websites.

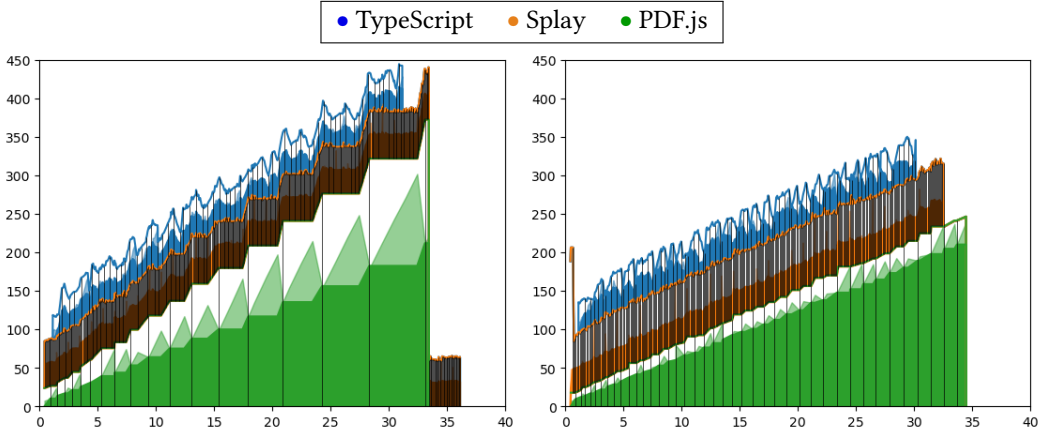


Fig. 2. Heap limit and usage plots for the three JetStream 2 benchmarks using either V8's current heap limit algorithm (on the left) or MemBalancer (on the right). Time runs along the horizontal axis (in seconds) and memory use along the vertical axis (in megabytes). Both plots use the same axes; the MemBalancer run (on the right) uses less memory and finishes faster. Each benchmark is shown in a different color (as described by the legend) and consists of three values: the live memory (dark color), current heap memory usage (light color) and current heap limit (white). A black line is drawn on each thread when it collects garbage. MemBalancer allocates less memory to PDF.js and more memory to Splay. Because Splay collects garbage very often, this trade is profitable, reducing garbage collection time and memory usage.

Table 1. In the first four columns, point-in-time estimates of L , g , and s for the three JetStream 2 benchmarks, taken relatively early into a MemBalancer run with $c = 20.0\%/MB$. In the next six columns, measurements of usable heap space $M - L$, total garbage collection time, and total benchmark run time for both MemBalancer and current V8 runs. Note that the $M - L$ columns for MemBalancer and current V8 are a point-in-time measurement (from similar but slightly different points during the benchmark run), while the total garbage collection time and total benchmark run time reflect the whole run. MemBalancer allocates the most usable heap space to the Splay benchmark, while current V8 allocates the most to PDF.js. As a result, MemBalancer reduces garbage collection time for Splay while increasing it for PDF.js, resulting in lower total garbage collection time.

Benchmark	L (MB)	g (MB/s)	s (MB/s)	Current V8			MemBalancer		
				$M - L$ (MB)	GC time (s)	Run time (s)	$M - L$ (MB)	GC time (s)	Run time (s)
splay.js	31	633	525	30	77	36	50	51	32
typescript.js	30	57	440	28	4.0	30	21	5.9	30
pdfjs.js	96	34	383	79	4.6	33	22	11	33
Total	158	725	1350	138	85	100	95	68	96

usable heap space than PDF.js; according to our model (Section 4), roughly $\sqrt{0.3 \cdot 18/1.4} \approx 2.1$ times more.⁶ However, V8's current heap limit rule is based mainly on live memory size and allocates the most usable heap space to PDF.js benchmark. This are visible in Figure 2, with PDF.js's portion of the plot becoming shorter, with more garbage collections, but the TypeScript and Splay portions becoming taller, with fewer garbage collections. Note that Splay still collects garbage roughly $8.9\times$ more often than PDF.js, since it allocates memory $18\times$ faster but only has $2.1\times$ more extra memory. This more-frequent collection is optimal, because Splay also allocates much more memory than the other two benchmarks.

⁶Note that the numbers in Table 1 do not exactly match this computation due to smoothing.

When we talk about “allocation”, keep in mind that neither current V8 nor MemBalancer have a central controller that allocates space; instead, this allocation is the emergent result of individual threads making heap limit decisions using local heap limit rules. Of course, both the current V8 heap limit rule, and MemBalancer, are configurable; V8’s current rule has dozens of tweakable parameters, which we left at their default values, and MemBalancer also has a tweakable c parameter, which we chose to be $c = 20.0\%/MB$. Naturally, tweaking these parameters could cause V8 to use less memory, or alternatively to use more memory and thereby spend less time collecting garbage. However, no matter how these parameters are tweaked, because V8’s current heap limit rule is not compositional, it will always overallocate memory to PDF.js and under-allocate memory to the other two threads, meaning that there is some parameter that causes MemBalancer to use both less memory and less time. That’s because the emergent memory allocation depends on structural features of the heap limit rule, not specific tuning parameters.

3 V8 GARBAGE COLLECTOR BACKGROUND

This section describes the overall architecture of the V8 garbage collector with a focus on heap limit rules. V8 is a state-of-the-art JavaScript runtime widely used in desktop, mobile, and server-side computing to power web applications, mobile apps, and back-end services. While Google Chrome is V8’s most prominent client, desktop applications built with the Electron framework (such as Slack, Discord, Spotify, and VS Code), mobile applications built with the Android WebView component (such as WeChat, Facebook, and Amazon), and server-side applications built with node.js and Deno all use V8.

Web browser users typically use tabs to view multiple websites, meaning that a single Chrome instance hosts multiple V8 JavaScript runtimes, known as “Isolates”.⁷ These runtimes typically run in different processes⁸ for reliability, performance isolation, and security. The security consideration has recently become more important, with CPU vulnerabilities such as Spectre [Agarwal et al. 2022] shown to be exploitable on the web. Because web pages are untrusted and mutually antagonistic, it’s essential that, insofar as possible, no communication occurs between Isolates. Each Isolate therefore contains its own heap and makes all decisions, including heap limit decisions, independently.

Because web applications are famously memory-hungry, web browsers use carefully engineered, high-performance garbage collectors tuned for high throughput and low pause times. V8 uses a generational garbage collector with one young generation (nursery) approximately 10 MB in size that uses mark-copy collection, and one old generation that uses mark-compact collection. Minor garbage collections are triggered when the nursery runs out of space; they happen every few seconds. This paper instead focuses on the old generation and major garbage collections.

Major garbage collections in V8 are complex, with optimized mark and sweep phases. To reduce pause times, in addition to a classical stop the world collector, V8 uses an incremental marking algorithm with a Dijkstra-style write barrier [Degenbaev et al. 2018b, 2019]. This means that the marking phase can be run in small chunks and interlaced with program execution. When the program makes modifications to the object graph, it updates the GC state atomically to ensure that the live/dead state for each object (the object’s “color”) is accurate. Incremental marking phases then propagate those colors through the object graph. Importantly, incremental marking means that most of the heap does not need to be traversed during the non-concurrent final marking phase, since it already has the correct color.

⁷Moreover, a single browser tab can host content from multiple sites via features like `<iframe>`, and a single site can start multiple independent and concurrent JavaScript heaps using features like WebWorkers.

⁸In Google Chrome, tabs from different *origins* (the part of the URL before the path) always run in different processes, while tabs from the same origin may or may not run in different processes. Other browsers such as Firefox and Safari use fewer processes, but still attempt to minimize communication between tabs for security reasons.

Incremental marking is run concurrently with the mutator thread, that is, the JavaScript program itself. This reduces pause times on the mutator thread and is the preferred way to do marking. However, incremental marking results need to be finalized before the compaction phase can start. This non-incremental, non-concurrent mark phase is started when the heap limit is reached, but is typically fast because most colors are accurate as a result of incremental marking. This combination of concurrent incremental marking and non-concurrent non-incremental finalization minimizes pause times.

Both the marking and compaction phases are also parallelized across multiple threads. Together with incremental and concurrent marking, these garbage collector features make it difficult to talk about total garbage collection time. This paper uses internal V8 APIs to compute the total collection time across all incremental marking phases, the final non-incremental marking phase, and the compaction phase. These APIs track total CPU time across all threads.

V8 sets old generation heap limits dynamically after every garbage collection. At a high level, V8 has two heap limit rules: setting the heap limit to a fixed multiple of live size, or adjusting the heap limit over time with a target of garbage collection being 3% of total running time. The fixed multiple rule forms a cap on the heap limit derived via the 3% rule. In the framework of Section 4, both of these rules result in a heap limit that is directly proportional to live size, so neither rule is compositional in our framework. Many additional factors make minor adjustments on top of these two high-level rules; for example, laptop and phone builds of V8 set heap limits slightly differently. These competing rules and adjustments reflect the fact that V8's current memory limit formula is not based on any formal model of optimal memory limit, and therefore must balance competing concerns in a fundamentally ad-hoc way.

One challenge with adjusting heap limits after garbage collection is that a thread can become idle—for example, a web application can be waiting for user input—while holding on to a large amount of dead memory [Degenbaev et al. 2016]. V8 therefore contains an intermittent “memory reducer” process that attempts to trigger garbage collection during idle times. Specifically, the memory reducer triggers additional major garbage collections based on factors like a low allocation rate, no frame being rendered by the browser, and memory pressure being present. Additionally, the memory reducer runs more often in background tabs and when a larger portion of the current heap limit is being used. The memory reducer determines when and how often to fire based on a complex boolean formula and a state machine that adjusts its behavior over time.

Finally, the Blink process monitors total system memory usage to avoid overwhelming system resources. When system resources are close to being exhausted (according to platform-specific operating system APIs) it notifies each V8 heap via a “memory pressure” notification. Upon receiving such a notification, V8 immediately performs a mark-compact garbage collection and returns all free pages to the operating system. In our experiments, to avoid noise from memory pressure notifications and isolate tabs from each other, we use a machine with enough memory that memory pressure is never a concern.

Within Google Chrome, V8 is one of several key components. Another is the rendering engine, Blink, which stores web page data and draws the web page to the screen. Blink objects live in their own memory space, but can both be referenced from JavaScript (such as when a JavaScript object stores a reference to an HTML element in the web page) and also reference JavaScript objects in turn (such as when an HTML element stores a JavaScript callback). Therefore V8 also has a second garbage collector for rendering engine objects, which coordinates with the main V8 garbage collector [Degenbaev et al. 2018a]. While work is ongoing to merge the two garbage collectors in V8, at the moment they operate largely independently. This paper focuses on garbage collection on the JavaScript heap, and so ignores browser-side objects except to account for their presence when computing heap limits and heap usage statistics.

One thing worth noting is that V8 is optimized for low-memory devices such as mobile phones, which causes different trade-offs than server-side run-times such as JVMs. For example, in server-side run-times the live memory is typically a fraction of total heap size to minimize garbage collection time; V8 uses much more conservative heap limits, and typically keeps the live memory to 60–80% of total heap size. This means that heap limit rules have a numerically-smaller effect on total heap size, since most of the heap will typically be taken up by live objects. However, this also suggests that memory is at a premium, and therefore that even small reductions in memory use are valuable to users.

4 COMPOSITIONAL HEAP LIMIT RULES

Our key insight is that every heap limit rule induces an allocation of memory across multiple heaps. With a single heap, all heap limit rules are pareto-optimal because they all merely pick a point that trades off memory usage for garbage collection time; but with multiple heaps, the induced allocation need not be pareto-optimal. A *compositional* heap limit rule induces a pareto-optimal allocation of memory across multiple programs.

To derive a compositional heap limit rule theoretically, consider a simple model of multiple garbage-collected language runtimes running simultaneously on a single computer. For concreteness, imagine that it is a multi-tab browser where each tab runs JavaScript and has a stop-the-world mark-compact garbage collector. In our model, each browser tab runs JavaScript that allocates memory at a fixed rate until that tab's heap limit is breached. At that point, JavaScript execution stops and garbage collection runs. While V8's mark phase can run concurrently with JavaScript, this model is still a close match because, thanks to incremental marking, mark phases are typically fast and the stop-the-world compaction phase dominates.

Consider a single garbage collection cycle that starts with L bytes of live memory and a heap limit of M bytes. Throughout the cycle, JavaScript first runs for t_m seconds, followed by t_g seconds of garbage collection. If JavaScript allocates memory at an average rate of g , then in t_m seconds it allocates gt_m memory, which must be equal to $M - L$. Assume furthermore that the garbage collector's running time is proportional to L at a fixed garbage collection speed s ; this is, again, a rough match to V8's compaction phase.

Variable	Meaning
L	Live memory
g	Allocation rate
s	Garbage collection speed
M	Heap limit

Fig. 3. Variables used in our theoretical model.

Putting these assumptions together, this garbage collection cycle involves $t_m = (M - L)/g$ seconds of JavaScript run time and $t_g = L/s$ seconds of garbage collector run time. To total this up across multiple heaps, which start and stop each garbage collection cycle at different times, we amortize garbage collection time over the full length of the cycle. Of our overall running time, a $t_g/(t_m + t_g)$ fraction is spent in garbage collection. If we assume that $t_m \gg t_g$, this simplifies to:⁹

$$\text{ratio} := \frac{t_g}{t_m} = \frac{L}{s} \frac{g}{M - L}$$

Note that s , g , and L are all program-specific parameters that cannot be controlled directly. However, M , the heap limit, is an arbitrary parameter.

⁹This assumption can be dropped, and the resulting heap limit rule is very similar; it is merely the square root rule derived in this paper, multiplied by a factor of $s/(s + g)$. Since garbage collection speed is faster than the allocation rate, this factor is typically close to 1, and dropping it does not impact the heap limit much.

The goal is now to choose M optimally. Since the browser has multiple tabs, the objective is to minimize the sum $\sum \text{ratio}$ across all the tabs by optimally choosing each tab's heap limit M . To do so, consider the derivative of ratio with respect to M . This derivative $\partial \text{ratio} / \partial M$ represents the “exchange rate” between a larger heap limit and a lower percentage of running time spent on garbage collecting; it is measured in $\% / \text{MB}$ or some equivalent unit. For $\sum \text{ratio}$ to be minimized, a kind of “no-arbitrage condition” needs to hold: reducing one tab's heap limit by a tiny amount and then increasing another tab's heap limit by the same amount should not impact $\sum \text{ratio}$. Therefore, $\partial \text{ratio} / \partial M$ must be equal for all tabs.¹⁰ Taking this derivative symbolically yields

$$-\frac{\partial \text{ratio}}{\partial M} = \frac{Lg}{s(M-L)^2} \quad (1)$$

For a heap limit rule to be compositional, this must equal the same constant c for all heaps.

Standard heap limit rules are not compositional. Specifically, if M is set to a multiple $(\alpha + 1)L$ of live memory, then c is equal to $g/s\alpha^2 L$, which differs for heaps with different g , s , and L . Of course, for a single heap, tuning α appropriately can achieve any heap limit. However, multiple heaps with the same α can only achieve certain combinations of heap limits, and those combinations do not include the combination that minimizes total garbage collection time. This demonstrates how considering multiple heaps places strong constraints on heap limit rules.

Returning to Equation (1), solving for M in terms of c yields:

$$M = L + \sqrt{Lg/cs} \quad (2)$$

Amazingly, all parameters involved in Equation (2)—the garbage collection speed s , the allocation rate g , and the live memory L —are local to a single heap. Equation (2) therefore defines a heap limit rule—one that “coordinates without communicating”, achieving an optimal allocation of memory across heaps without any communication between those heaps. This “square-root” rule has the expected heap limit behaviors:

- (1) Tabs that have more live memory (with large L) should have more “extra memory” $M - L$, since each garbage collection has a higher “fixed cost” from traversing the live memory.
- (2) Tabs that allocate more quickly (with large g) should have a higher memory limit, since they hit that limit more often.
- (3) Tabs whose heaps can be mark-compacted more quickly (with large s) should have a lower memory limit, since garbage collections are less costly.

In other words, as expected, an optimal memory limit allows more memory to tabs that need more memory, produce garbage faster, and collect garbage slower.

But crucially, the square-root heap limit rule allocates “extra memory” $M - L$ to each tab proportional not to L , g , and s , but to their square-roots. This is the key to minimizing total garbage collection time across multiple heaps. Compared to standard proportional heap limit rules, the square-root rule results in lower heap limits for heaps with large live memory (high L), and higher heap limits for heaps with small live memory (low L); in other words, it is **sublinear**.¹¹ Heaps that allocate a lot (high g) or are slow to collect garbage (low s) also get higher heap limits with the square-root rule, since it takes these factors into account. Of course, the c parameter can be changed to increase or decrease overall memory usage, just like tuning the constant of proportionality in a proportional heap limit rule.

In practice, a compositional heap limit rule can also improve performance for a single heap. In our model, program behavior (g , L and s) is invariant over time. However, real-world programs change

¹⁰This optimization problem can be solved more formally using the method of Lagrange multipliers.

¹¹Firefox's TraceMonkey JavaScript runtime uses a proportional heap limit rule, but with smaller constants of proportionality as the live memory increases. This potentially approximates the optimal square-root rule behavior.

their behavior over time, such as first loading data and then executing. A standard, proportional heap limit rule will give too high a heap limit when L is large and too small a heap limit when L is small. A compositional heap limit rule, by contrast, will minimize total garbage collection time across the full program execution.

This paper focuses on the square-root rule where c is a fixed constant. That said, Equation (1) allows c to vary as long as it is the same for all heaps at any given point in time. One could imagine a centralized controller that adjusts c up and down to use all available system resources without causing swapping, as in [Alonso and Appel \[1990\]](#). Or, c could vary based on whether or not a phone is charging or using battery.

Another possibility is to optimize for something other than total garbage collection time. For example, garbage collection time on different heaps can be *weighted*, with background tabs having a lower weight. Then the c value for a tab should be proportional to one over each tab's weight.¹² These options show that, despite its strictness, Equation (1) admits a lot of flexibility.

5 A SQUARE-ROOT RULE ALGORITHM

At a high level, implementing the square-root heap limit rule of Equation (2) is straightforward: measure L , g , and s for each tab and compute $M = L + \sqrt{Lg/cs}$ from those values. However, two challenges need to be resolved for to put this idea into practice.

The first challenge is defining and measuring the live memory L , average allocation rate g , and average garbage collection speed s . The challenge is that, while g is observable in real time (thanks to a simple counter incremented by the allocator), s and L are not. Handling this requires a multi-threaded design. Because g can be observed in real time, a “heartbeat” thread wakes once a second to record the current allocation rate g and re-compute the heap limit M . This can raise or lower the heap limit; if the heap limit is lowered below the current heap size, a garbage collection will be triggered later by V8. By contrast, L and s are not observable in real time, and can only be measured accurately immediately after a garbage collection.¹³ Our proposed approach, which we call MemBalancer, therefore measures L and s on the main thread after every major garbage collection, recording L and s and recomputing the heap limit M . Major garbage collections also measure and update g to avoid measuring g across major GC boundaries. As a result, heap limits are updated at least once per second, or more often if garbage collections are frequent.

The second challenge is prediction. In the model of Section 4, the s value in Equation (2) represents the time to collect garbage at the *end* of the current cycle, so it is fundamentally a predictive value. Similarly, g measures the average allocation rate over the current cycle, so is again a predictive value. Moreover, both s and g change as the program executes, so their estimated values need to react to changes; but both are measured based on run times, so need to dampen noise. MemBalancer therefore smooths the new allocation data using an exponentially weighted moving average, which estimates a value as a weighted linear combination of the current value and the last estimate. For g , a smoothing constant of $\alpha_g = 0.95$ is used, so that the half-life of any data point is about thirteen seconds, which reduces jitter enough to prevent spurious garbage collections but still allows the rate g to respond rapidly to changes in program behavior. Similarly, the measured s is smoothed, with a smoothing constant of $\alpha_s = 0.5$, to account for anomalously long garbage collections. Both g and s are measured by dividing a number of bytes by a duration; as is standard, we smooth the top and bottom individually.

¹²The derivation is similar to that for Equation (2).

¹³Actually, due to incremental GC, multiple inter-related heaps, and other details of V8, a garbage collection may not clear out all dead objects, meaning that L might not be precisely observed. In practice, however, the memory left after garbage collection is mostly live objects, so makes for a good-enough estimate of L .

$s_m^*, s_t^*, L^*, g_m^*, g_t^* = 0, 0, 0, 0, 0$
def on_gc(s_m, s_t, L) :

 $s_m^* = \alpha_s s_m^* + (1 - \alpha_s) s_m$
 $s_t^* = \alpha_s s_t^* + (1 - \alpha_s) s_t$
 $L^* = L$
def on_heartbeat(g_m, g_t) :

 $g_m^* = \alpha_g g_m^* + (1 - \alpha_g) g_m$
 $g_t^* = \alpha_g g_t^* + (1 - \alpha_g) g_t$
def compute_M(M) :

$$E = \sqrt{\frac{L^* g_m^* / g_t^*}{c s_m^* / s_t^*}}$$

 $M = L^* + \max(E, E_{min}) + M_{nursery}$

Input	Meaning
L	Live memory after collection complete
s_m	Bytes collected during collection
s_t	Collection duration
g_m	Memory allocated since last heartbeat
g_t	Time since last heartbeat
Variable	Meaning
x^*	Smoothed estimate of variable x
c	MemBalancer tuning parameter
M	Computed heap limit
Constant	Meaning
α_g	.95, smoothing factor for g^*
α_s	.5, smoothing factor for s^*
E_{min}	2 MB, minimum extra heap space
$M_{nursery}$	10 MB, nursery size

Fig. 4. On the left, pseudocode for the MemBalancer algorithm. On each major garbage collection, on_gc() is run after the collection, followed by on_heartbeat() and then compute_M(). Once a second on a heartbeat thread, on_heartbeat() is run, followed by compute_M(). On the right, the meaning of all of the inputs, variables, and constants used by MemBalancer.

6 IMPLEMENTATION IN V8

We instantiated this high-level algorithm for the V8 JavaScript virtual machine, basing our prototype on a stable version of V8 from 7 June 2022 (commit hash b1413ed7). Broadly speaking, our V8 prototype of MemBalancer follows the high-level algorithm in Figure 4. The V8 Heap constructor creates an additional heartbeat thread for each heap. This heartbeat thread wakes once per second to record the current heap memory usage (using the SizeOfObjects() API in V8) and time since last update. This is compared to the previous record (stored in new Heap member fields) which is smoothed and written to atomic member fields on the Heap, as in on_heartbeat() in Figure 4. Every time a major garbage collection occurs, the main thread uses the existing GCTracer API to measure live memory L and garbage collection speed s . Garbage collection speed is smoothed and then both values are written to two other atomic member fields on the Heap, as in on_gc() in Figure 4. The member fields are atomic to ensure reliable communication between the two threads; using atomic variables instead of a mutex is important for keeping pause times low. After either kind of update, the heap limit is recomputed following compute_M() in Figure 4. Because each Isolate has its own heartbeat thread, multiple heaps in a process (such as multiple WebWorkers) do not communicate any information and are performance-isolated.

We use environment variables to enable MemBalancer and set the c parameter. This is convenient for experiments, but in a production implementation, these values could be hard-coded, set by compilation flags, or passed to V8 by Blink through V8's options API or through Blink's Performance Manager API. For example, "V8 Lite" builds, intended for low-memory environments, could use larger values of c to trade more garbage collection time for less memory use. All told, our prototype of MemBalancer requires roughly 200 lines of modifications to V8 (plus a couple dozen lines of logging code).

Internal V8 invariants required minor changes to Equation (2). V8 doesn't quite garbage collect when the heap limit is reached; instead, it garbage collects when the remaining space on the heap

would be less than the nursery size. We therefore add the nursery size, 10 MB to the heap limit computed by MemBalancer before setting it as the V8 heap limit. We also noticed that, since web applications were event-driven, they typically had long periods of idleness in between computations. During an idle period, no memory is allocated, meaning that the estimated g decreases smoothly toward 0. When another event occurs, the heap limit is breached immediately, causing a garbage collection. This could cause an out-of-memory situation if g is low enough that that garbage collection does not significantly raise the heap limit. We therefore added a minimum usable heap memory limit E_{min} to MemBalancer, meaning that its heap limit is always set to at least the live memory L plus 2 MB. When a new event comes in, MemBalancer has enough time to measure a new g value and update the heap limit before it is breached. While these tweaks mean that MemBalancer is not a strictly compositional heap limit rule, the excess is only a few megabytes per tab, much smaller than other per-tab fixed costs within the browser and similar to V8's current heap limit rule.¹⁴

Thanks to MemBalancer's principled heap limit rule, our prototype can remove V8 components that patch over issues with a purely proportional heap limit rule. A common pattern in web applications is that the application idles until a user event occurs. Once user input occurs, the application runs, allocating and using memory, until it is done responding to the event and returns to idleness. Applications also make network requests and idle until a response comes back. Such applications need to be garbage-collected to ensure they don't needlessly hold on to garbage.

In V8 currently, the heap limit is only updated when a major garbage collection occurs. To avoid idle heaps retaining memory, V8 thus has a separate memory reducer process that periodically triggers garbage collections when a thread is idle and not allocating [Degenbaev et al. 2016]. However, tuning this memory reducer process is difficult; if it runs too often, it wastes time collecting garbage from only temporarily-idle threads, while if it runs less often threads retain garbage for too long.

By contrast, MemBalancer adjusts the heap limit at a steady one-second cadence as its estimate of g changes, much more often than the memory reducer is triggered. When a thread goes idle, its estimated g decays exponentially (due to the exponentially weighted moving average) and thus so does its extra memory. This quickly leads to a garbage collection, collecting garbage memory from the idle thread. This supersedes the memory reducer, which we could then remove. MemBalancer triggers these idle-time garbage collections earlier and less frequently than the memory reducer would, leading to lower memory usage and lower garbage collection time.

To aid evaluation of V8 heap limit rules, we built a garbage collection logging system for V8. Each Heap writes to a private log file every time a major garbage collection occurs and every time the heartbeat thread measures g . This allows reconstructing allocation and garbage collection behavior. Because it involves access to the file system, this logging system requires turning off the V8 sandbox and would not be advisable in a production-ready implementation. Aggregated log files could instead be made available through the browser's built-in developer tools, potentially giving web developers granular information about L , g , and s that they could use to further improve the application's performance.

7 EVALUATION

We evaluate MemBalancer on the ACDC-JS garbage collection microbenchmark and on real-world websites, demonstrating substantial reductions in garbage collection time and average heap usage.

¹⁴V8 currently ensures, for example, that all heaps have at least 2MB of heap memory unused, increasing that to 8MB as memory becomes available.

7.1 Microbenchmarking with ACDC-JS

We evaluate MemBalancer against V8's current heap limit rule using the ACDC-JS benchmark suite [Aigner et al. 2014]. ACDC-JS is an existing JavaScript garbage collection benchmark that simulates real-world heap shapes. The heap shape is chosen via a set of tuneable parameters, including object liveness and object size, which affect our L and s parameters. (ACDC-JS's other parameters affect structural properties of the object graph with less direct impact on MemBalancer.) Given these parameters, ACDC-JS allocates and deallocates objects in a tight loop, so that almost all run time is spent in the JavaScript runtime's allocator and garbage collector. It thus makes a challenging test of MemBalancer's impact on program run time. For our test we chose four threads corresponding to (object size, object liveness) of (8, 1) (8, 16) (64, 8), and (64, 128). We tune each run to take approximately 1 minute and leave all other parameter values at their default.

We evaluate both MemBalancer and current V8 on total garbage collection time and average heap memory usage.¹⁵ Garbage collection time is measured using the standard V8 GCTracer API. Only major garbage collection time is included, and for incremental garbage collection, both the concurrent, incremental mark phase and the finalization phase are measured and added together. Heap memory usage uses the V8 `SizeOfObjects()` and `ExternalMemoryAllocatedSinceMarkCompact()` APIs to track total object size in the old generation. This definition of heap memory usage does not account for fragmentation, though we expect the effect from this to be small except in cases of extremely low memory, because V8 uses a mark-compact garbage collector that keeps fragmentation low. Non-heap-allocated objects like jitted code or feedback vectors are not included in this measure. Heap memory usage is measured once per second on each V8 isolate and all measurements are reported and averaged to compute the average heap memory usage. Both garbage collection time and heap memory usage are then summed across the four threads.

Comparing MemBalancer to current V8 requires care because different c values will cause MemBalancer to have different average heap usage and garbage collection time. We therefore compare the current V8 heap limit algorithm (the baseline)¹⁶ against MemBalancer with different values of c ranging from 0.1 %/MB to 10.0 %/MB. MemBalancer is superior to current V8 if the range of heap usage / collection time trade-offs achievable by MemBalancer is superior to the heap usage and collection time of current V8.

The results are shown in Figure 5, which shows garbage collection time and average heap usage for MemBalancer (blue) and current V8 (black). To estimate the improvement in average heap usage, we also estimate a regression line based on the model in Section 4. Figure 5 shows the regression line as well as a 95% confidence interval (two standard errors) around the regression line.

Depending on the value of the parameter c , MemBalancer either has less average heap memory usage, less total garbage collection time, or both. This clearly indicates that on these benchmarks, MemBalancer is strictly superior to the baseline. If a value of c is chosen so that MemBalancer uses roughly the same amount of memory as the baseline, MemBalancer achieves a reduction of about 30.0% garbage collection time; if c is chosen so that MemBalancer spends roughly the same amount of time in garbage collection, MemBalancer achieves a reduction of about 8.2% average heap usage.

7.2 Macrobenchmarking with Real-world Websites

We demonstrate MemBalancer's effectiveness on real-world websites by integrating our modified V8 version with a Chromium (the open-source project behind Google Chrome) checkout from 9 June

¹⁵We run our experiments on a machine with an i7-5820k 12-core CPU (at 3.30GHz) and 16GB of DDR4 memory running Zorin OS 16.1, a Linux distribution based on Ubuntu 20.04.2 LTS.

¹⁶Note that current V8 does not have an easily tunable parameter for garbage collection frequency, so each run of the baseline produces a single measurement, not a trade-off.

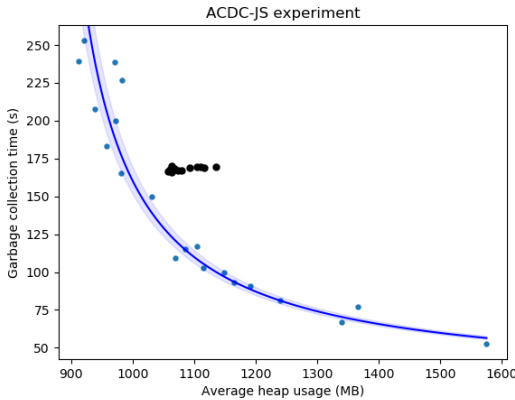


Fig. 5. MemBalancer and current V8 on ACDC; Each point on the scatter plot corresponds to a single run of the ACDC-JS experiment; blue points use MemBalancer (with different c values) and black points use current V8 (with identical parameters). Some MemBalancer runs strictly dominate all current V8 runs, meaning that MemBalancer achieves a better trade-off than current V8. The relatively tight dispersion of black dots shows that measurement noise has little effect on the results.

2022 (commit hash b13d3f). This allowed us to evaluate MemBalancer on six popular American websites: Facebook, Gmail, Twitter, Fox News, CNN, and ESPN. For each website, we wrote simple mock user scripts using Pypeteer, a Python port of the browser automation library Puppeteer. Each user script sends user input to the website and then waits for a fixed amount of time to allow the website to finish responding to it. For CNN, Twitter, ESPN, Fox News and Facebook our script scrolls down by 50 pixels every second. These websites have an “infinite scroll” feature, meaning that scrolling down causes the website to load more news stories from the server and render them on the page using JavaScript. For Gmail, our script opens and closes emails, spending 10 seconds in the inbox and 5 seconds on each email. This causes Gmail to repeatedly load and render email contents and the inbox, both of which require significant JavaScript execution. It also waits 5 seconds upon loading to emulate an initial user pause. For Facebook, we open the Facebook “Group” page and scroll the infinite scrolling feed on that page. (We initially planned to test more web pages, including Reddit and several more news sites. However, these sites banned our computer’s IP, likely due to anti-bot countermeasures, so we had to remove these sites from our evaluation.) Because these benchmarks take longer to run than ACDC-JS, we test a narrower range of c values between 0.05 %/MB and 0.9 %/MB.

Facebook, Gmail, and Twitter require log-ins to function. We manually log in to fresh accounts before starting the experiments, to ensure that we get past any CAPTCHAs and so log-in actions are not measured. On Twitter and Facebook, we chose common topics to “follow” to ensure that the feed contains a lot of content. We used our Gmail account to register for Twitter and Facebook, so it contains many complex emails. Each website continues taking actions until three minutes have elapsed. Since garbage collection time is typically a small fraction of overall website running time and our scripts include relatively long waits, this results in similar work being done no matter the heap limit rule.

Because users typically have multiple tabs open, including multiple active tabs, our evaluation loads and runs multiple websites simultaneously. Each run is therefore identified by the set of websites opened across tabs. We test all websites individually, all thirty pairs of websites, and thirty randomly chosen triples of websites. When multiple websites are run independently, the last website opened is the “active” tab. This distinction is important, because inactive tabs do not need to be rendered to the screen (an activity that blocks JavaScript from running) and also disable or reduce the capabilities of certain APIs (for example, timers fire less often). In the current V8, the memory reducer also triggers more garbage collection in inactive tabs. All tabs use the same c

parameter, and we run multiple runs of each website group with different c values. For each run, we measure average heap usage and total garbage collection time.

For each benchmark, we use live websites and a full Chrome instance, meaning that the results are roughly representative of real-world usage. But this also means that some noise is inevitable, whether due to live A/B testing or different results from ad auctions or any other reason. Chrome is also a complex, massively concurrent software system causing additional noise. Unfortunately, eliminating this noise is not possible without significantly modifying Chrome, which would call into question our experiment's external validity. Therefore we restrict our main research question to how often MemBalancer points strictly dominate current V8, and how often the reverse occurs. This determination should be less affected by noise.

Our results are shown in Figure 6, grouped experiments into three sets of plots: for one-tab, two-tab, and three-tab experiments. As for the ACDC-JS experiments, the scatter-plot shows average heap usage on the horizontal axis and garbage collection time on the vertical axis, with different colors representing different website combinations. Additionally, to make different website combinations comparable, the current V8 runs are averaged and the data is then normalized so that that average current V8 run sits at (1, 1).

Across all three experiments, far fewer points are located in the top-right quadrant (where MemBalancer uses more average heap space and more garbage collection time) than in the bottom-left quadrant (where MemBalancer uses less average heap space and less garbage collection time). This demonstrates that MemBalancer is superior to V8's current heap limit rule. We can estimate the relative improvement of MemBalancer over current V8 by estimating a regression line based on the data points. To do so, we aggregate every data point from every run and use ordinary least squares to estimate the trade-off curve, under the assumption that it follows the model in Section 4. The regression line passes substantially below the reference point, again indicating that MemBalancer is superior to V8's current heap limit rule. Considering the regression line's intersections with the axes, we find that MemBalancer saves 67.0% of garbage collection time or 11.0% of average heap usage for one tab, 49.0% of garbage collection time or 16.0% of average heap usage for two tabs, and 48.0% of garbage collection time or 16.0% of average heap usage for three tabs.

Note that the two-tab and three-tab experiments achieve larger reductions in average heap usage than the single-tab experiments. With a single tab, memory allocation across tabs is a non-issue, explaining the lower savings. But we speculate that the one-tab experiment still shows some reduction in average heap usage due to inter-temporal trade-offs. That is, V8's current heap limit computation causes a single tab to use too much memory (compared to MemBalancer) at some points in time, and then too little memory (compared to MemBalancer) at other points in time. MemBalancer in effect "trades off across time", decreasing both average heap usage and total garbage collection time.

7.3 Threats to validity

Both the ACDC-JS and real-world experiments demonstrate that MemBalancer improves on V8's current heap limit rule, achieving a better trade-off between average heap usage and total garbage collection time. Moreover, both sets of experiments show a large and significant effect, corresponding to a reduction of approximately 10% of average heap usage. The main threats to the validity of this result are noise and representativeness.

Regarding noise, our real-world experiments used live websites and thus were subject to variation from network timings or even different website contents. This noise makes it difficult to accurately estimate the overall improvement in average heap usage and total garbage collection time, with our estimates derived from regression lines that make strong assumptions about the data. Nonetheless, even the real-world experiments clearly have more points where MemBalancer strictly dominates

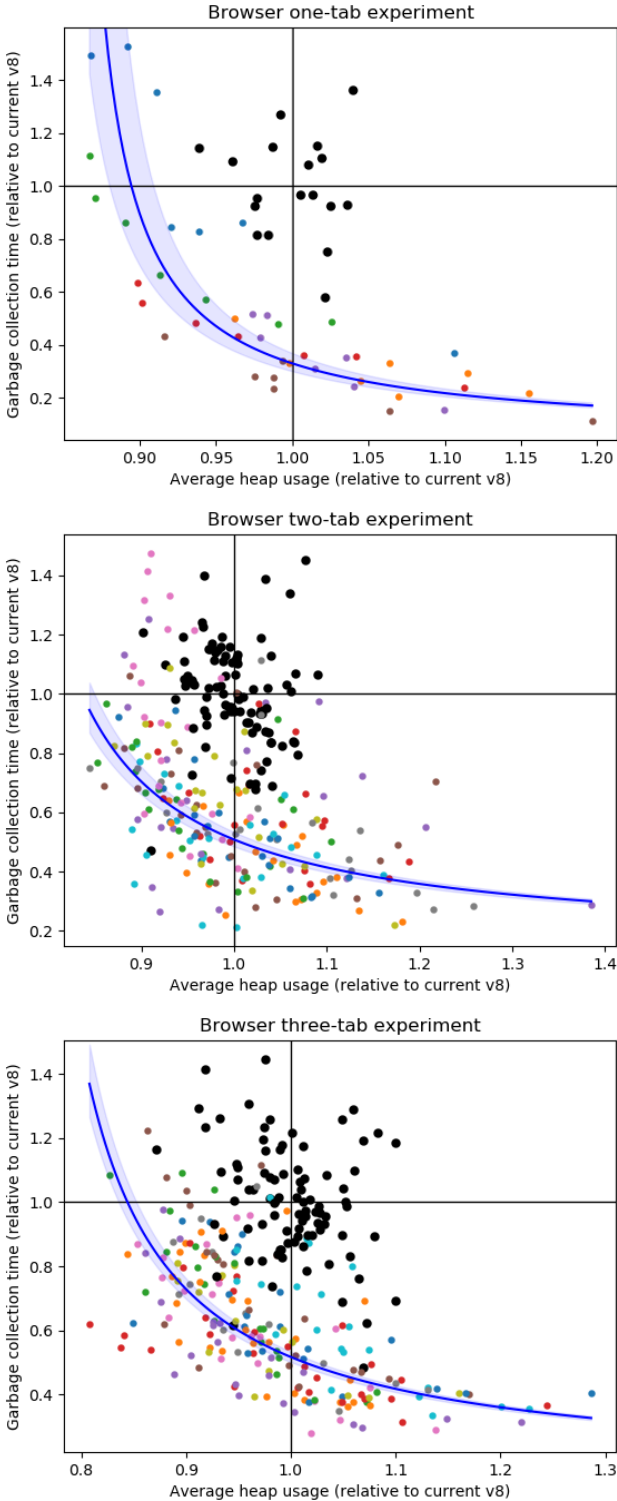


Fig. 6. Results of MemBalancer on six real-world websites, with either one, two, or three websites open at a time and either MemBalancer (at different c values) or current V8 (run multiple times with identical parameters) as the heap limit rule. Each plot measures average heap usage on the horizontal axis and total garbage collection time on the vertical axis. Both axes are normalized so that the average base-line run for a given set of web pages is located at (1, 1). Each colorful dot represents a single MemBalancer run, with a fixed c value and a fixed set of open web pages; each black dot represents a single baseline run using current V8 with the default parameters. Compared to Figure 5, the black dots are much more widely dispersed, reflecting the fact that each run will see different network timing, concurrency, or page content. A regression line plus a two-standard-error confidence interval is also drawn. Almost all of the black dots are above and to the right of the regression line, meaning that MemBalancer reduces garbage collection time and heap memory usage compared to current V8. Furthermore, MemBalancer’s advantage seems to increase and the variance seems to decrease as the number of simultaneous tabs increases.

current V8 than vice versa, demonstrating that the effect is positive. Moreover, the ACDC-JS experiment avoids most of these sources of noise, with both current V8 and MemBalancer points closely spaced, demonstrating that noise does not drive the results.

Regarding representativeness, the ACDC-JS experiment is based on a microbenchmark that spends its time almost exclusively in allocation and garbage collection. However, our real-world website evaluations use websites responsible for billions of daily active users, and our user scripts execute common user actions. Naturally, the set of evaluation websites could be expanded, and the universe of web pages is extremely diverse.¹⁷ That said, the combination of real-world and microbenchmark results already strongly supports the conclusion that MemBalancer is superior to V8's current heap limit rule in practical applications.

Finally, our results evaluate MemBalancer and current V8 on average heap usage and total garbage collection time. However, users may have more complex desires. For example, users may care less about garbage collection time on background tabs. MemBalancer could accommodate this preference by using a larger c value for background tabs, but we do not evaluate this. Users may also have additional preferences around peak memory usage, maximum garbage collection pause times, fragmentation, or other qualities not controlled by MemBalancer. Modeling and integrating these into MemBalancer is a possible direction for future work.

7.4 Deploying MemBalancer

Firefox. MemBalancer is likely applicable to JavaScript runtimes besides V8. For example, the Firefox SpiderMonkey JavaScript engine, like V8, uses a collection of heuristics to choose its heap size. In Firefox, a thread can use one of two different heap limit rules: a “high frequency” limit (when the garbage collector is run often) and a “low frequency” limit. Moreover, while the heap limit rule works by multiplying the live memory by a fixed constant (proportional), the constant of proportionality decreases as the live memory increases. In other words, the heuristics used by Firefox already approximate some structural features of MemBalancer. Moreover, the mix of heuristics introduces problems; for example, allocating slightly more or less often can cause a program to switch from the low-frequency to the high-frequency rule due to the hard cut-off between them. The developers believe this is a cause of undesired garbage collection behavior [Mozilla 2022]. The Firefox developers have implemented MemBalancer and are testing its effects on Firefox's performance with the aim of making it the default heap limit algorithm.

Racket. We sent a preprint on this paper to Matthew Flatt, a core developer for the Racket programming language [Flatt and PLT 2010]. He implemented a simplified version of the square-root rule that sets $M = L + c\sqrt{L}$ and tested it on his preferred Racket benchmark, a single-threaded batch-mode build of Racket and related libraries and documentation. Previously, Racket used a simple proportional rule with $M = 2L$. The simplified square-root rule lowers memory use by 10% while incurring a 1-2% slowdown. Note that multi-threaded or multi-process Racket programs, which weren't directly evaluated, would likely show larger gains. The Racket developers also tested a version of the square root rule more similar to MemBalancer, including smoothed measurements of g and s , but the results were no better. That could be because Racket program execution is more uniform than web pages. Similarly, the Racket version of the square root rule did not use a heartbeat threads because idleness is less common for Racket programs. The new square-root rule heap limit was merged into mainline Racket [Flatt 2022] and released as part of Racket 8.5.

¹⁷Though note that, due to anti-bot scripts and other protections, evaluating on real-world websites is challenging.

8 RELATED WORK

Fast and efficient garbage collection has been studied for decades. Garbage collection was invented in 1959 for the Lisp programming language [McCarthy 1960]. The canonical survey of the field is the Garbage Collection Handbook [Jones et al. 2012].

The first garbage collector, for the Lisp programming language, limited the heap to 15 000 cons cells and triggered garbage collection when this heap was exhausted [McCarthy 1960]. Already, the trade-off between heap memory usage and garbage collection is noted: “[garbage collection’s] efficiency depends upon not coming close to exhausting the available memory with accessible lists” [McCarthy 1960]. At the time, the heap limit simply reflected available core memory (time-sharing operating systems not yet being in common use) and so was not configurable by the user. Today, of course, garbage-collected languages often allow the user to configure the heap limit to maximize performance in the presence of other programs running on the same machine. Such manual tuning may be necessary to achieve maximal performance [Shang 2020] but is complex and requires substantial expertise.

The system most similar to MemBalancer is Alonso and Appel [1990]’s “advice server”, published decades ago. The advice server uses a model of garbage collection similar to that in Section 4 to estimate the impact of different heap limits, and adjusts heap limits across multiple heaps to reduce total garbage collection time. Like MemBalancer, the advice server measures g and s during program run time, and they note a similar square-root dependence. Unlike MemBalancer, heap limits are changed only after garbage collections, and smoothing for g and s is not investigated. This means the advice server requires longer program run times—30 minutes instead of 3 minutes. More importantly, the advice server is a centralized server that attempts to adjust overall memory usage to consume all available system resources. This requires a fully trusted environment. The notion of a compositional heap limit rule, however, sidesteps the need for a centralized server, replacing it with coordination without communication. If matching overall memory usage to system resources is desired, the advice server could advise processes on the choice of c instead of directly controlling memory usage. We do not know of any current uses of the “advice server” model.

Modern garbage-collected languages have automatic heap limit rules to adjust the heap limit based on program behavior. Typically, the heap limit is set to be a multiple of live memory (or, equivalently, the fraction of time spent on garbage collection is held to a constant) [Oracle 2015]. Hertz and Berger [2005] analyze such rules for a collection of different garbage collection algorithms and find that multiples as large as $3\times$ or $5\times$ are necessary to reduce the overhead of garbage collection to negligible levels, though modern garbage collectors typically use lower multiples.

Since greater heap limits improve performance, determining the maximum possible heap limit is useful. Several papers introduce dynamic heap limit rules to determine the greatest heap limit that does not cause paging [Brecht et al. 2006; Hertz et al. 2011; Yang et al. 2004; Zhang et al. 2006]. Avoiding paging is particularly important because garbage collection can trigger worst-case behavior in paging algorithms, though garbage collectors can be designed to avoid this problem [Hertz et al. 2005]. Another line of work introduces a central controller that can make allocation decisions across multiple programs. Cameron et al. [2015], for example, measures Pareto curves for virtual machines and combines them to achieve the best possible trade-off between memory and garbage collection time. This data-driven approach works well for virtual machines, where long run times provide lots of data. In a browser, where programs have a short lifetime, a model-based approach like MemBalancer is required.

More broadly, heap limit rules are merely one instance of the ever-present space-time trade-off. This paper can be seen as automatically tuning one class of such trade-offs, but there are many others. GCCache, for example, balances a Java application’s software cache against its garbage

collector [Nunez et al. 2016]. The M3 system proposes a mechanism similar to V8’s Memory Pressure Notifications to coordinate cache sizing across multiple applications [Lion et al. 2021]. Similar trade-offs are common throughout garbage-collected language runtimes; for example, in a jitted runtime, optimized code generation affects both runtime and memory use [Alle et al. 2019]. Rematerialization, a compiler technique for reducing memory pressure, is a similar challenge, done statically [Briggs et al. 1992]. Kirisame et al. [2021] does something similar, though dynamically, for machine learning workloads.

9 CONCLUSION

This paper proposes that garbage-collected language runtimes should use a compositional heap limit rule to guarantee that multiple heaps allocate memory amongst themselves in a way that minimizes garbage collection time. Standard heap limit rules, unfortunately, are not compositional, so we derive a compositional “square-root” limit rule, describe an algorithm that instantiates it, and implement that algorithm for V8 in a system called MemBalancer. On both memory-intensive benchmarks and real-world websites, MemBalancer leads to a significantly better trade-off between memory usage and garbage collection time. On real world websites, reductions in average heap memory usage of up to 16.0% are possible without increasing garbage collection time.

In the future, we hope to evaluate compositional heap limit rules for other virtual machines. The other major JavaScript engines, Spidermonkey (used in Firefox) and JavaScriptCore (used in Safari), are natural fits, since both involve have multiple heaps when the user opens multiple tabs. Investigating MemBalancer’s impacts on server-side JavaScript frameworks such as node.js and Deno is also important; it’s unclear if server-side applications show larger or smaller gains than web applications. Compositional heap limit rules are also applicable to other languages, as demonstrated by the deployed Racket implementation. (Though, as in the Racket implementation, language-specific simplifications may be appropriate.) We are excited for experiments on other common language runtimes, such as in JVMs. Most intriguingly, we hope to test whether compositional heap limit rules allow coordinating virtual machines for different languages, when for example a Racket program runs simultaneously with a web browser.

Theoretical improvements could also refine the notion of compositional heap limit rule. Adding a model of memory fragmentation could allow better memory management in low-memory situations such as cheap smartphones. A model of multiple generations could allow optimally sizing both the young and old generations, which could lead to further speed-ups. Empirical work such as [Hertz and Berger 2005] suggests that minor garbage collections have a different analytical model of run time so different heap limit rules would be compositional. A model of garbage collection latency could reduce pause times and determine when to schedule concurrent marking phases such as those in V8. A model of heap priorities could capture real-world valuations such as background tabs being less important than foreground tabs in a web browser. Finally, automatically adjusting c to account for system memory usage, latency requirements, or other criteria could potentially make MemBalancer even more effective.

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