NG2C: Pretenuring N-Generational GC for HotSpot Big Data Applications

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Abstract

Big Data applications suffer from unpredictable and unacceptably high pause times due to Garbage Collection (GC). This is the case in latency-sensitive applications such as on-line credit-card fraud detection, graph-based computing for analysis on social networks, etc. Such pauses compromise latency requirements of the whole application stack and result from applications’ aggressive buffering/caching of data, exposing an ill-suited GC design, which assumes that most objects will die young and does not consider that applications hold large amounts of middle-lived data in memory.

To avoid such pauses, we propose NG2C, a new GC algorithm that combines pretenuring with an N-Generational heap. By being able to allocate objects into different generations, NG2C is able to group objects with similar lifetime profiles in the same generation. By allocating objects with similar lifetime profiles close to each other, i.e. in the same generation, we avoid object promotion (copying between generations) and heap fragmentation (which leads to heap compactions) both responsible for most of the duration of HotSpot GC pause times.

NG2C is implemented for the OpenJDK 8 HotSpot Java Virtual Machine, as an extension of the Garbage First GC. We evaluate NG2C using Cassandra, Lucene, and GraphChi with three different GCs: Garbage First (G1), Concurrent Mark Sweep (CMS), and NG2C. Results show that NG2C decreases the worst observable GC pause time by up to 94.8% for Cassandra, 85.0% for Lucene and 96.45% for GraphChi, when compared to current collectors (G1 and CMS). In addition, NG2C has no negative impact on application throughput or memory usage.

Categories and Subject Descriptors D.3.4 [Programming Languages]: Processors - Memory Management (garbage collection)

Keywords Garbage Collection, Big Data, Latency

1. Introduction

Big Data applications are now part of the application stack present in most (if not all) large-scale systems. These applications are expected to work with high volumes of information efficiently and often run on top of platforms such as Cassandra, Lucene, GraphChi, etc. This is the case of latency-sensitive applications such as on-line credit-card fraud detection, graph-based computing for analysis on social networks or the web graph, etc.

To achieve good performance, developers often resort to optimization techniques to boost performance such as caching [51][54][50]. Caching is used to keep (in memory): i) the working set or intermediate results [59] (this is a common practice, for example, in graph processing systems such as GraphChi [37] and Spark [58]), or ii) consolidate writes in a database (for example, in-memory tables in Cassandra [38]). With caching, developers avoid costly operations such as re-computing intermediate values (in the case of GraphChi and Spark) or writing records to disk (in the case of Cassandra), among others. However, while keeping more data in memory helps reducing the latency for data requests, it puts more pressure on the Garbage Collection (GC) which results in long pauses of the application [10][49].

GC pauses are unpredictable (from the application’s perspective) and can stop the application for an unacceptably high amount of time leading to broken Service Level Agreements (SLAs) [16][48][52]. The is even worse if the application stack contains multiple managed heaps. If only one GC engages in a long GC pause, the whole stack is compromised and the SLA is broken.

By analyzing applications running on the HotSpot JVM, it is possible to conclude that the duration of GC pauses is dominated by the number and size of objects to copy in memory during a GC (this problem is also described in Gidra [21][22]). Such copies can be triggered by object promotion or by a heap compaction (to reduce fragmentation). The problem with copying is that it is bound to the available hardware memory bandwidth. Increasing the capacity of nodes (e.g., the number of cores) will not reduce neither the number nor the duration of GC pauses.

Therefore, the widely accepted weak generational hypothesis stating that most objects die young [31][33][57] (which is a fundamental design rule for current HotSpot GCs) is not suited for many Big Data applications. As a matter of fact, such applications try to fit their working set in memory, leading to a high number of objects that live for a long period of time (from the GC perspective). This mismatch between the objects’ real lifetime and the GC assumption that most objects die young has serious consequences for HotSpot applications with high memory utilization and tight response time targets (i.e., SLAs to cope with).

Avoiding object copying within the heap cannot (or is extremely hard to) be attained by tweaking the heap or GC parameters; thus, many application developers end up (almost) reverse engineering the GC to understand how to avoid costly GC pauses in their applications [59] (with obvious software development productivity drawbacks). Another important difficulty is that a particular GC/heap configuration will only work for a specific environment (number of cores, size of memory, etc.), making a particular configuration not replicable.

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Pretenuring is also a well studied technique [6, 12, 13, 27, 34, 42]. The main problem with these solutions is that simply pretenuring objects to a single older space (old generation) leads to heap fragmentation since objects with different lifetime profiles are promoted to the same space, NG2C, opposed to previous pretenuring works, uses an N-Generational heap that groups objects with similar lifetime profiles in the same generation. This reduces object promotion and heap fragmentation. See Section 2 for more details.

In order to use NG2C, object allocation sites must be annotated to indicate in which generation the object should be allocated. To free the developer from the burden of understanding the objects’ lifetime profiles, we developed a profiler tool, Object Lifetime Recorder (described in Section 3.5) that profiles the application and outputs where and how the code should be changed in order to take full advantage of NG2C (note that the application only needs to be proﬁled once).

NG2C is implemented for the OpenJDK 8 HotSpot Java Virtual Machine (JVM) as an extension of the next OpenJDK by-default GC, Garbage First (G1). Results are very encouraging as we are able to achieve our goal: avoid costly object copying (which occurs during object promotion and compactions). NG2C decreases the highest observable GC pauses by up to 94.8% for Cassandra, 85.0% for Lucene and 96.45% for GraphChi, when compared to current collectors: G1 and CMS (Concurrent Mark Sweep). In addition, application throughput and memory usage are not negatively affected by using NG2C.

To sum up, our main contributions are: i) the identiﬁcation of the scalability problem of current HotSpot GCs which rely on object copying, ii) a new GC algorithm, NG2C, that combines an arbitrary number of generations with pretenuring to avoid object copying and heap fragmentation, iii) an implementation of NG2C and the Object Lifetime Recorder (OLR) proﬁler tool on a production JVM, OpenJDK 8 HotSpot, and iv) the evaluation of the performance beneﬁts of using NG2C on Big Data platforms (Cassandra, Lucene, GraphChi) using workloads and data sets based on real system utilization.

2. Related Work

NG2C proposes N-Generational pretenuring, where objects are pretenured into different generations, according to their lifetime proﬁle. By allocating objects in different generations, per-lifetime proﬁle, NG2C reduces object promotion and heap fragmentation. Since this work combines several well studied ideas, we dedicate this section to explaining how our research relates to previous work.

Generational Collectors

Segregating objects by age has been studied for a long time [32] as a way to take advantage of the weak generational hypothesis [57]. By promoting objects that survive a number of collections into older generations, the collector can concentrate on collecting younger generations more often (since these are more likely to contain more dead objects) [40]. The use of multiple generations (compared to using a single generation) has been shown to reduce application pauses [7, 30, 43, 53].

Opposed to previous works such as the Beltway framework [7] and the Mature Object Space collector [29], NG2C does not promote/copy objects gradually through older generations since this only generates more object copying (which we are trying to avoid). Instead, objects are pretenured based on the object lifetime proﬁle.

Pretenuring and Object Demographics

Pretenuring is also a well studied technique [6, 12, 13, 27, 34, 42]. It consists on allocating objects (that are known to live for a long time) directly in older generations. By doing this, the overhead associated to object promotion is avoided. The key problem to pretenuring lies on how to estimate the lifetime proﬁle of an object (analyzed next).

To the best of our knowledge, no pretenuring algorithm has been combined with an N-Generational collector. If a collector with predefined number of generations is used (for example, two generations), pretenuring does not solve heap fragmentation, as middle-long lived objects with different lifetime proﬁles might be pretenured to the same heap location. To solve this problem NG2C combines pretenuring with multiple generations. By being able to pretenure into an arbitrary number (deﬁned at runtime) of generations, NG2C avoids fragmentation. Thus, by combining these two techniques, object copying (which results from object promotion and compaction) is greatly reduced.

Pretenuring is tightly coupled with object lifetime proﬁling, which is used to extract object lifetime estimations, used to guide pretenuring. Extracting objects demographic information can either be performed dynamically [13, 27, 34] or statically [6, 12, 32]. Profiling information can come from stack analysis [12, 13], connectivity graphs [25] and can also include other program’s traces [42].

Our proposed profiler, (presented in Section 3.5) builds upon previous works [6, 12, 32] by resorting to stack analyzes. However, opposed to previous works, it accurately estimates in which generation an object should be allocated in. In other words, our proﬁler answers the question of how long will the object probably live while previous profilers only tell us if the object will probably live enough to be considered old (this information is not sufﬁcient to take advantage of an N-Generational heap).

Region-based Garbage Collection

The hypothesis that many objects, allocated in the same scope, share the same faith, i.e., have similar lifetimes has also been leveraged by many region-based memory management algorithms [1, 4, 9, 15, 19, 20, 23, 24, 28, 35, 46]. In such algorithms, objects with similar lifetime proﬁles are allocated in scope-based regions, which are deallocated as a whole when objects inside these regions are no longer reachable. However, existing region-based algorithms either require sophisticated static analysis [1, 4, 9, 15, 19, 20, 23] (which does not scale to large systems), heavily rely on manual code refactoring [23, 46] (to guarantee that objects in the same region die approximately at the same time), or support only simple programming models [41, 46, 47] (such as parallel bag of tasks).

Other region-based collectors [18] use thread-local allocation regions to allocate objects. This approach also does not support more complex models where most large data structures can be maintained by multiple threads (for example, Cassandra’s in-memory tables).

NG2C can also be seen/used as a region-based collector, in which generations can be used as regions. However, opposed to typical scope-based regions, NG2C supports more complex programs such as storage platforms with minimal code changes.

Off-heap based Solutions

There are some solutions based on off-heap memory [41, 44, 46] (i.e., allocating memory for the application outside the GC-managed heap). While this is an effective approach to allocate and keep data out of the range of the GC (and therefore, reducing object copying), it has several important drawbacks: i) off-heap data needs to be serialized to be saved in off-heap memory, and de-serialized before being used by the application (this obviously has performance overheads); ii) off-heap memory must be explicitly collected by the application developer (which is error prone [11, 14] and completely ignores the advantages of running inside
NG2C is designed to profit from information regarding objects’ lifetime profiles (as described in Section 3.3) this information is provided by the OLR profiler). Thus, NG2C co-locates objects with different lifetime profiles in different generations.

Since applications might have multiple threads/mutators managing objects with different lifetime profiles (e.g., processing separate jobs), each thread must be able to allocate objects in different generations.

To efficiently support parallel allocation in multiple generations, we bind each application thread into a specific generation using the concept of current generation. The current generation indicates the generation where new objects, allocated with the @Gen annotation, will be allocated into. In practice, when a thread is created, its current generation is 0. If the thread decides to create a new generation, this will change the thread’s current generation to the new one. It is also possible to get and set the thread current generation.

More specifically, the application code can use the following calls (see Listing 1):

- `newGeneration()`, creates a new generation and sets the current generation of the executing thread to the newly created generation;
- `getGeneration` and `setGeneration`, gets and sets (respectively) the current generation of the executing thread.

To allocate an object in the current generation, the new operator must be annotated with @Gen. All allocation sites with no @Gen will allocate objects into Gen 0 (see Figure 1).

The code example in Listing 2 resembles a very simplified version of graph processing systems (e.g., GraphChi). It shows a method that runs several tasks in parallel threads. Each thread starts by calling `newGeneration`, to create a new generation. Then, while the task is not finished, all allocated objects using the @Gen annotation will be allocated in the new generation.

Listing 3 shows a code example that resembles a very simplified version of memory buffers in storage systems such as Cassandra; it shows how to use NG2C to allocate a large data structure (e.g., a buffer to consolidate database writes or intermediate data) while avoiding object copying. The constructor creates a new generation in which the buffer is allocated (using the @Gen annotation).

Starting from Java 8, the new operator can be annotated. We use this new feature to place a special annotation that indicates that this object should go into the thread’s current generation.

1. Starting from Java 8, the new operator can be annotated. We use this new feature to place a special annotation that indicates that this object should go into the thread’s current generation.
public class Buffer {
    byte[][] buffer;
    Generation gen;
    Buffer() {
        gen = System.newGeneration();
        buffer = new @Gen byte[N_ROWS][ROW_SIZE];}
}

Algorithm 1 Memory Allocation - Object Allocation

1: procedure OBJECT_ALLOCATION
2: size ← size of object to allocate
3: klass ← class of object to allocate
4: isArray ← object is of array type?
5: gen ← current thread generation
6: isGen ← new operator annotated with @Gen?
7: if isGen then
8: tlab ← TLAB used for generation gen
9: else
10: tlab ← TLAB used for Gen 0
11: if isArray then
12: goto slow path
13: if end(tlab) − top(tlab) > size then
14: object ← init(klass, top(tlab))
15: bumpTop(tlab, size)
16: return object
17: slow path:
18: if size > size(tlab)/8 then
19: returnALLOC IN REGION(klass, size)
20: else
21: returnALLOC IN TLAB(klass, size)

Algorithm 2 Memory Allocation - Allocation in Region

1: procedure ALLOC IN REGION(klass, size)
2: gen ← current thread generation
3: isGen ← new operator annotated with @Gen?
4: if isGen then
5: region ← gen alloc region
6: else
7: region ← Gen 0 alloc region
8: if end(region) − top(region) > size then
9: object ← init(klass, top(region))
10: bumpTop(region, size)
11: return object
12: if isGen then
13: region ← new gen alloc region
14: else
15: region ← new Gen 0 alloc region
16: if region not null then
17: object ← init(klass, top(region))
18: bumpTop(region, size)
19: return object
20: else
21: trigger GC and retry allocation

3.3 N-Generational Memory Allocation

NG2C allows each thread to allocate objects in any generation. This is fundamentally different from current HotSpot’s allocation strategy which assumes that all newly allocated objects are placed in the young generation. Hence, in order to support N-Generational object allocation, we extended the allocation algorithm to be able to allocate objects in multiple generations.

In NG2C, object allocation is separated in two paths: i) fast allocation path, using a Thread Local Allocation Buffer (TLAB) and ii) slow allocation path (array or very large object allocation).

Allocations through the slow path are handled in one of two ways: inside a TLAB (if there is enough free space), or directly in the current Allocation Region (AR) outside a TLAB. Note that for each generation, there is one AR.

The high level algorithm is depicted in Algorithms 1 and 2. For the sake of simplicity, and without loss of generality, we keep the algorithm description to the minimum, only keeping the most important steps.

A call to Object Allocation starts an object allocation. If the allocation is marked with @Gen, the allocation takes place in the current generation which is available from the executing thread state (otherwise the object is allocated in Gen 0). Arrays automatically fall into the slow path while regular objects are promptly allocated from the TLAB unless there is not enough space.

Large object allocation (objects larger than a specific fraction of the TLAB size) goes directly to the current AR of the current generation (or Gen 0 if the allocation is not annotated). If the region has enough free space to satisfy the allocation, the object is allocated. Otherwise, a new region is requested from the available regions’ list within the heap. If no memory is available for a new region, a GC is triggered followed by an allocation retry. If a GC is not able to free enough memory, an error is reported to the application.

The pseudocode for allocations in TLABs is not shown because of space restrictions. Nevertheless, the code between lines 7 and 16 is already representative of how allocations inside a TLAB are conducted.

3.4 N-Generational Memory Collection

In NG2C, three types of collections can take place (see Figure 2):

- minor collection: triggered when Gen 0 has no space left for allocating new objects. Collects the Gen 0. Objects that survived a number of collections (more details in Section 3.3) are promoted to the Old generation;
- mixed collection: triggered when Gen 0 has no space left for allocating new objects and the total heap usage is above a config-

\(^2\) A TLAB is a Thread Local Allocation Buffer, i.e., a private buffer where the thread can allocate memory without having to synchronize with other threads.

\(^3\) An Allocation Region is used to satisfy allocation requests for large objects and also for allocating TLABs. Whenever an AR is full, a new one is selected from the list of available regions.
incremental dumps using CRIU, a Checkpoint/Restore tool for Linux profiling) of the Java heap (where all the application objects reside). We create

A Java Agent is a small pluggable component that can be attached to the JVM, being able to analyze its state.

Survivor objects from any of the collected memory regions (excluding memory regions from the Old generation), are promoted to the Old generation. Please note that, in a mixed collection, although all the regions belonging to Gen 0 are collected, regions belonging to other generations are only collected if the percentage of live data is below a configurable threshold. In addition to collecting multiple regions from multiple generations, a mixed collection also triggers a concurrent marking cycle (described next);

- full collection: triggered when the heap is nearly full. Collects the whole heap. In a full collection, all regions belonging to all generations are collected. All survivor objects are promoted to the Old generation.

Note that when all regions that compose a generation are collected, the generation is discarded. If future allocations that target a specific generation that was previously discarded, the target generation is re-created before the first allocation is actually performed.

In a concurrent marking cycle (that starts during a mixed collection), the GC traverses the heap and marks live objects. As the name indicates, most of this process is done concurrently with the application. When the marking phase ends, the GC frees all regions containing only unreachable (i.e., unmarked) objects. For the regions that still contain reachable content, the GC saves some statistics (used for example in mixed collections) on how much memory can be reclaimed if a particular region is collected.

### 3.5 Object Lifetime Recorder

To enable developers to take full advantage of NG2C, we developed the Object Lifetime Recorder (OLR) profiler, a HotSpot JVM profiler that records object allocation sites and lifetimes. Using OLR, no developer’s knowledge is required to change the code in order to take advantage of NG2C.

OLR is composed by three components (see Figure 3). First, the Allocation Recorder (implemented as a Java Agent) is used to: i) notify the JVM Dumper (second component, described next) when a collection finishes, and ii) record allocation sites. The second component, the JVM Dumper creates incremental heap dumps (regarding previous heap dumps, taken upon previous collections) whenever a collection finishes (the JVM Dumper is notified by the Allocation Recorder when a heap dump should be taken). Compared to other heap dump tools, for example, with the jmap tool, incremental dumps are smaller in size (as they contain only modified memory positions), thus leading to shorter application stop times for creating the heap dump.

The third component, the Object Graph Analyzer is used to process the allocation sites and heap dumps generated during the application profiling. Objects’ metadata (allocation timestamp, collection timestamp, and allocation site) is loaded into memory and an object graph is built. Then, the graph is processed in order to extract and present which objects should belong in the same generation, and where these objects are allocated.

In practice, even an inexperienced developer can change the source code of an application to take advantage of NG2C. The developer only needs to run the application using OLR’s Allocation Recorder and run the JVM Dumper. When the application finishes (or after running for some time under the normal/target workload), the developer launches the Object Graph Analyzer that outputs where and how the code should be modified. With this information, even an inexperienced programmer can change the code locations suggested by the OLR in minutes.

We measured a performance cost (throughput) of up to 4 times when running the profiler on the systems we use in the evaluation. However, note that the profiler only has to run once and that the code changes proposed by the profiler lead to significant performance improvements in production settings (as observed in Section 3). In other words, despite the fact that the profiler analyzes the application with reduced throughput, the captured allocation and collection patterns hold true in a production setting.

### 4. Implementation

NG2C is implemented on top of the Garbage First (G1) GC [17]. G1 is the most recent and advanced GC algorithm available for the OpenJDK HotSpot JVM 8. In addition, G1 is the new default GC in the HotSpot JVM. NG2C builds upon G1, by adding approximately 2000 LOC. NG2C is integrated with G1 in the way that applications that do not use the @Gen annotation will run using the G1 collector (i.e., the code introduced by NG2C is never activated). This has the great benefit that all the effort put into developing G1 ensures that NG2C works with the same performance to G1 for all applications. For the rest of this section, we describe how we modified G1 for supporting N-Generational pretuning.

By using G1’s as our code base, we inherit many techniques that are already well implemented and tested. In other words, we are using all the GC techniques already implemented in G1 (such as remembered sets management, safepoints, write barriers, and concurrent marking) to support NG2C’s implementation.

G1 uses a heap divided in equally sized memory regions. It contains two generations, the young and the old. The young generation is divided into three spaces (Eden, and two survivor spaces, To, and From). In NG2C, Gen 0 corresponds to the young generation in G1 (including the three spaces composing it). The old generation corresponds to NG2C’s Old generation. Additional generations are created by allocating regions from the free memory regions list (also available in G1). The existing code in G1 looks at NG2C’s additional generations as part of G1’s old generation. This means that we reuse G1’s write barrier and remembered set for inter-generational pointers.

NG2C’s inherits G1’s collector algorithms without almost any change. Minor, mixed, and full collections work in the exact same way in both NG2Cand G1. The only modification is that, in NG2C, the collector can promote objects from different generations into the Old generation, while in G1, the collector either only promotes from young to old or compacts regions belonging to the old generation.

Most of the code introduced by NG2C, lies in the object allocation path. In the next sections we describe how the new alloca-
tion algorithm works and how the byte code interpreter and Just-In-Time compiler are adapted to work with it.

4.1 Parallel Memory Allocation

Contention in memory allocation is a well-known problem\(^\text{[20]}\)\(^\text{[32]}\). Memory allocation must be synchronized between threads so that each memory block is used by a single thread. In G1 this is achieved by using Thread Local Allocation Buffers (TLABs) and Allocation Regions (ARs). Therefore, whenever a thread needs to allocate some memory, it allocates directly from its TLAB. If the TLAB is full, the thread must allocate memory from the current AR. This allocation, however, will only occur after the thread acquires a lock on that AR. If the AR does not have enough available space, a new AR is allocated directly from the list of free regions (this step requires even further locking to ensure that no other thread is allocating another region).

In NG2C, we extend the use of both TLABs and ARs to multiple generations (the complete algorithm is presented in Section 3.3). Since each thread can now allocate memory in multiple generations, multiple TLABs are necessary to avoid costly memory allocations. The TLAB to use for each allocation is decided at runtime, based on the use of \@Gen annotations (see Section 4.2 for more details). Additionally to TLABs, NG2C also extends the use of ARs to multiple generations. Therefore, when a TLAB used for a particular generation is full, an allocation request is issued directly to the AR of the specific generation.

By using multiple TLABs and ARs (one for each generation), allocations are more efficient as fewer synchronization barriers exist compared to not using (TLABs and ARs). This, however, introduces a problem: as any thread can allocate memory in any generation, each thread must have a TLAB in each generation (even if that thread never allocates memory in that particular generation). As the number of generations grows, more and more memory is wasted for allocating TLABs that are never actually used.

To solve the aforementioned problem, NG2C never actually allocates any memory for TLABs when we create a new generation. Memory for each TLAB is effectively allocated only upon the first allocation request. This way, threads will have TLABs (with allocated memory) only for the generations that are being used (and not for all the existing generations).

4.2 \@Gen Annotations

For allocating memory in generations other than Gen 0, we considered several options: i) simply calling the JVM to switch the generation to use for allocation; ii) add a new new operator with an extra argument (target generation); iii) annotate the new operator.

We opted for the last option for the following reasons. The first was immediately ruled out because it is very difficult to control which objects go into non-young generations; e.g., naïve String manipulation can easily result in many allocations that would potentially go into a non-young generation. The second option (creating a new allocation operator) would force us to extend the Java language, and the compiler.

A clear advantage of using annotations is its simplicity; however, it has one disadvantage: we must call the JVM whenever we need to change the current target generation. However, in practice and according to our experience, this almost never imposes a relevant overhead because: i) a thread handling a particular task will most probably only need one generation (worker threads tend to use one generation at a time), and ii) large object allocation and copying is much more expensive than calling the JVM to change the target generation (therefore it pays off to allocate a large object in the correct generation). In both cases, the cost of calling the JVM is absorbed and the overhead becomes negligible (see Section 5 where we show that NG2C does not decrease the application throughput). Also note that getting and setting the current generation does not require any locking as it only changes a field in the current thread’s internal data structure.

4.3 Code Interpreter and JIT

The OpenJDK HotSpot uses a combination of code interpretation and Just-in-Time (JIT) compilation to achieve close to native performance. Therefore, whenever a method is executed for the first time, it is interpreted. If the same method is executed for a specific number of times, it is then JIT compiled. This way, the JVM compiles (a costly operation) only the methods where there is benefit (since executing compiled code is much faster than interpreting it).

In order to comply with such techniques in NG2C, we modify both the interpreter and the JIT compiler to add the notion of generations. To be more precise, we had to detect if the allocation is annotated with \@Gen and, if so, which generation is being targeted (choose the correct TLAB).

Selecting the correct TLAB to allocate is done as follows. For each thread, NG2C keeps a pointer to the current generation TLAB. This pointer is only updated when the thread calls newGeneration or setGeneration. Then, if the current allocation site is annotated with \@Gen, the current generation TLAB is used.

Detecting if the current allocation is annotated with \@Gen is done differently before (interpretative mode) and after JIT compilation. Before JIT, we use a map of byte code index to annotation, that is stored along the method metadata (this map is prepared during class loading). Using this map, it is possible to know in constant time if a particular byte code index is annotated with \@Gen or not. Upon JIT compilation, the decision of whether to go for Gen 0 or not is hardcoded into the compiled code. This frees the compiled code (after JIT) from accessing the annotation map.

5. Evaluation

We now evaluate the performance of NG2C while comparing it with G1, CMS. We also have results for C4. Although not being an OpenJDK collector, C4 comes from a similar JVM, Zing\(^\text{[5]}\). Since we only have on license available, we could not run all experiments with it.

We use three relevant platforms that are used in large-scale environments: i) Apache Cassandra 2.1.8\(^\text{[38]}\), a large-scale Key-Value store, ii) Apache Lucene 6.1.0\(^\text{[43]}\), a high performance text search engine, and iii) GraphChi 0.2.2\(^\text{[37]}\), a large-scale graph computation engine. A complete description of each workload, including how the source code was changed (with the help of OLR profiler), is presented in Section 5.4. Please note that we could not use the widely studied DaCapo\(^\text{[8]}\) benchmark suite since it does not compile for Java 8 (which is required for NG2C to work). Nevertheless, we could run SPECjvm2008\(^\text{[55]}\) benchmarks whose results are published online at github.com/rodrigo-bruno/ng2c.

For evaluating NG2C, we are mostly concerned on showing that, compared with other collectors, NG2C: i) does reduce application pause times; ii) does not have a negative effect on throughput nor for memory utilization; iii) greatly reduces object copying; iv) does not increase the remembered set management work.

5.1 Evaluation Setup

We evaluate NG2C in three different environments (Table 1 provides a summary of the evaluation environments). First, we use Feedzai\(^\text{[7]}\), an internal benchmark environment. This environment mir-

5 Zing is a JVM developed by Azul Systems (www.azul.com).
6 Feedzai (www.feedzai.com) is a world leader data science company that detects fraud in omnichannel commerce. The company uses near real-time machine learning to analyze big data to identify fraudulent payment transactions and minimize risk in the financial industry.
rors a real-world deployment and uses a Cassandra cluster to store data. For Feedzai, it is very important to keep Cassandra’s GC pauses as short as possible to guarantee that client SLAs are not broken by long query latencies. The Cassandra cluster is composed by 5 nodes.

Second, we use a separate node to evaluate NG2C with Cassandra under three different synthetic workloads with varying number of read and write operations (more details in Section 5.2.1): Write-Intensive (WI), Write-Read (WR) and Read-Intensive (RI).

Given the size of the data sets used for Lucene (Wikipedia dump) and GraphChi (Twitter graph dump), we use another separate node to evaluate NG2C. On top of Lucene we perform client searches while continuously updating the index (read and write transactions). For GraphChi, we use two workloads, PageRank and Connected Components. More details in Sections 5.2.2 and 5.2.3 (for Lucene and GraphChi workloads, respectively).

Each experiment runs in complete isolation for at least 5 times (i.e., until the results obtained become stable). Feedzai’s workload runs for 6 hours, while all other workloads run for 30 minutes each. When running each experiment, we never consider the first minute of execution (in Feedzai’s benchmarks we disregard the first hour of execution to allow other external systems to converge). This ensures minimal interference from JVM loading, JIT compilation, etc.

We always use fixed heap and young generation/Gen 0 sizes (see Table 1). We found that these sizes are enough to hold the working set in memory and to avoid premature massive promotion of objects to older generations (in the case of CMS and G1). Table 1 also reports the number of lines changed after using the OLR profiler.

### 5.2 Workload Description

We use this section to provide a more complete description of the workloads used to evaluate NG2C.

#### 5.2.1 Cassandra

We use Cassandra under 4 different workloads: i) Feedzai’s workload (consisting of 500 read queries and 25000 write queries per second, for the whole Cassandra cluster); ii) write intensive workload (2500 read queries and 75000 write queries per second); iii) read-write workload (5000 read queries and 5000 write queries per second); iv) read intensive workload (7500 read queries and 25000 write queries per second).

Note that Feedzai’s workload is based on representative data from real deployments of their product (i.e., fraud detection). All workloads besides Feedzai’s are synthetic but mirror real-world settings (e.g., we use the YCSB benchmark tool). When running Cassandra in Feedzai’s cluster, we setup the JVM with 30GB of heap and we fix the young generation (Gen 0 for NG2C) to 4GB.

We use Lucene to build an in-memory text index using a Wikipedia dump from 2015[9][10]. The dump has 31GB and is divided in 33M documents. Each document is loaded into Lucene and can be searched.

We use Lucene to build an in-memory text index using a Wikipedia dump from 2015[9][10]. The dump has 31GB and is divided in 33M documents. Each document is loaded into Lucene and can be searched.

The workload is composed by 20000 reads (document updates) and 5000 reads (document searches) per second; note that this is a write intensive workload which represents a worst case scenario for GC pauses. For reads (document queries), we loop through the 500 top words in the dump; this also represents a worst case scenario for GC pauses.

When running Lucene, we use all available cores (48 cores), the heap size is limited to 120GB with a 2GB young generation (Gen 0 for NG2C) size. Again, we tested with different heap sizes and we found out that this value is beneficial for short GC pauses.

To reduce Lucene’s GC pauses we profiled it with the OLR profiler. The code was mainly modified to allocate documents’ data (of the Wikipedia dump) in a single separate generation. Objects created to hold the indexes of documents will live throughout the application lifetime; therefore, if we do not use NG2C such objects would be copied within the heap (thus leading to long GC pauses).

With NG2C, most objects holding the index (including objects such as Term, RAMFile and byte buffers) are allocated outside Gen 0, i.e., in a separate generation. To accomplish it, we changed 8 code locations in Lucene, all of which to annotate the new operator.

#### 5.2.2 GraphChi

When compared to the previous systems (Cassandra and Lucene), GraphChi is a more throughput oriented system (and not latency oriented). However, we use GraphChi for two reasons: i) we want to demonstrate that NG2C does not decrease throughput even in a throughput oriented system; ii) with NG2C, systems such as GraphChi can now be used for applications providing latency oriented services, besides performing throughput oriented graph computations.

In our evaluation, we use two well-known algorithms: i) page rank, and ii) connected components. Both algorithms are feed with a 2010 twitter graph [12] consisting of 42 millions vertexes and 1.5 billions edges. These vertexes (and the corresponding edges) are loaded in batches into memory; similarly to Cassandra’s Memtables, GraphChi calculates a memory budget to determine

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8 The Yahoo! Cloud Serving Benchmark (YCSB) is an open-source benchmarking tool often used to compare NoSQL database systems.

9 A Memtable table buffers recent writes in memory. When a Memtable is full, a flush is scheduled and a new Memtable is created. The capacity of each Memtable is proportional to the JVM heap size.

10 Wikipedia dumps are available at dumps.wikimedia.org
the number of edges to load into memory before the next batch. This represents an iterative process; in each iteration a new batch of vertexes is loaded and processed.

When running GraphChi, we use all available cores (48 cores), the heap is limited to 120GB, and the young generation (Gen 0 for NG2C) is limited to 6GB (we measured with different sizes and we found that this provides the shortest GC pause times in the current environment and workload).

To take advantage of NG2C, we profiled GraphChi with the OLR profiler. The code was mainly modified to allocate objects representing graph vertexes (ChiVertex), edges (Edge), and internal pointers (ChiPointer) in multiple generations (one per batch). We modified a total of 9 code locations, in which we annotate the new operator.

### 5.3 GC Pause Times

Figure 4 presents the GC pause times for each GC (CMS, G1, and NG2C) and for each percentile, for all the workloads. We do not show pause times for C4 because it is a concurrent collector and therefore, the application should never be paused. In practice, using C4, we got pauses of only up to 15 milliseconds for Cassandra.

Figure 5: Number of Application Pauses Per Duration Interval (ms)

In Feedzai’s workload, CMS shows shorter GC pauses for lower percentiles but shows the worst results in higher percentiles (25% worse than G1 and 47% worse than NG2C). G1 shows more stable GC pause times (when compared to CMS) as it does not lead to long pauses in higher percentiles; NG2C shows GC pause times very similar to CMS in lower percentiles, and it shows shorter GC pause times for higher percentiles as well.

The other Cassandra workloads (WI, WR, and RI) differ only in the percentage of read and writes. From the GC perspective, more writes means that more objects are kept in memory (which results in more object copies and therefore longer GC pauses). This obviously applies to Cassandra because it buffers writes in memory. This is clearly observable by comparing the GC pauses across the three workloads (WI, WR, and RI) for CMS and G1. RI workload shows shorter GC pauses than WR and WI, while WR shows shorter pauses than WI but longer than RI. According to our results, CMS is more sensitive to writes (than the other two collectors) as it has a steep increase in the GC pause time as we move towards write intensive workloads. G1 has a more moderate increase in GC pause time in more intensive workloads.

Regarding NG2C, it produces a different behavior as it shows shorter GC pauses for lower percentiles in WI, and longer pauses for WR in higher percentiles. One factor contributes for this difference (between NG2C, and G1 and CMS): we profiled (using OLR profiler) Cassandra under the WI workload. This means that the
read path is not as optimized as the write path. Therefore, in write intensive workloads, NG2C is more optimized than in read intensive workloads. This is also observable by measuring the difference between the GC pause times in higher percentiles; as we move towards write intensive workloads, the difference between NG2C and other GCs increases.

We also have results for Cassandra with the off-heap memory enabled for CMS and G1 (Cassandra uses off-heap memory to store values while the keys remain in the managed heap). Using off-heap reduces GC pause times by up to 50% in the WI workload (versus 93.8% using NG2C), around 20% in the WR workload (versus 39% using NG2C), and shows no improvement for the RI workload (versus 61% using NG2C). In sum, using NG2C is more effective to reduce GC pause times than using off-heap memory mainly because Cassandra needs to keep header objects in the memory managed heap to describe the contents stored in off-heap. In the case of Cassandra (key-value store), keys are stored in the managed heap and therefore contribute for long application pauses. NG2C is able to move all key-value pairs into a specific generation (thus avoiding pause times).

The remaining workloads (Lucene, PR, and CC) are all write intensive. CMS shows very high GC pause times compared to the other two GCs. G1 shows a more moderate increase in GC pause times, when compared to CMS, but is still worse than NG2C. In sum, NG2C clearly improves the worst observable GC pause times by: 85% (CMS) and 38% (G1) in Lucene, 97% (CMS) and 84% (G1) in PR, and 97% (CMS) and 82% (G1) for CC.

Figure 8 presents the average and standard deviation for the number of pauses in different duration intervals. Results show that: i) NG2C does not increase the number of pauses, and ii) it moves pauses to smaller duration intervals. CMS presents the worst results by having the most amount of pauses in longer pause intervals.

5.4 Object Copy and Remembered Set Update

We now look into how much time is spent: i) copying objects within the heap, and ii) updating remembered set entries, upon a collection. Note that the remembered set updates is an important metric since pretenuring can lead to high number of remembered set updates because of the potential increase in the number of references coming from older to younger spaces [32]. We only show results for G1 and NG2C, given that CMS and C4 do not provide such logging information. However, both metrics are similar for different generational collectors because they mostly depend on: i) the mutator allocation speed (dictates how fast minor collections are triggered and how many objects are promoted), and ii) the available hardware memory bandwidth. Both these factors are kept constant across GCs (G1 and NG2C).

Figure 6 presents results for total object copying time and remembered set update time during each workload. All results are normalized to G1. Results show that NG2C reduces objects copying between 30.6% and 89.2%. Note that, in G1, we can not differentiate between object promotion and object compaction since the collector collects both young and old regions at the same time (during mixed collections). NG2C also has a positive impact for the remembered set update work. This means that, in NG2C, there is not an increase in the number of references from older generations into Gen 0. This is possible because objects referenced by pretenured objects are most likely to be promoted as well. NG2C even reduces the amount of remembered set update work for most workloads since it reduces the amount of premature promotion in G1 (objects with short lifetimes that were allocated right before a minor collection and were prematurely promoted). This also means that NG2C puts less pressure on the write barrier (compared to G1).

5.5 Memory Usage

In this section, we look into the max memory usage to understand how NG2C relates to other collectors regarding heap requirements (see Table 2). Regarding the workloads’ max heap size: Feedzai workload has 30GB, while the other Cassandra workloads (WI, WR, and RI) have 12GB; each Lucene and GraphChi’s workload (PR and CC) have 120GB.

From Table 2, we can conclude that, regarding Cassandra workloads (i.e., Feedzai, WI, WR, and RI) all collectors (excluding C4) have a very similar max memory usage. CMS has a slight smaller heap compared to G1 and NG2C while NG2C has a slight larger heap compared to G1 and CMS. This slight increase comes from the fact that generations are only collected upon a mixed collection, which is only triggered when the heap usage is above a configurable threshold. This can lead to a slight delay in the collection of some objects that are already unreachable, C4 has a considerable higher memory usage since it reserves approximately 75% (12GB) of the system’s memory, when the JVM is launched. We were unable to extract the actual memory usage during execution. We do not show the results for C4 with other workloads because we only have one license (for one physical node).

Lucene max memory utilization is lower for CMS compared to G1 and NG2C. These larger heap sizes in G1 and NG2C comes from humongous allocations. Using this technique, very large objects are directly allocated in the old generation. It has the clear drawback of delaying the collection of such very large objects. Since CMS does not have such technique (i.e., all objects are allocated in the Eden), CMS tries to collect these large objects upon each minor collection, leading to faster collection of such objects, thus achieving lower heap usage. Comparing G1 with NG2C, the heap usage is similar.

Regarding GraphChi, which shows a different memory behavior when compared to Cassandra and Lucene, it allocates many small objects (which therefore are not considered for humongous allocation in G1 and NG2C). Most of these small objects (mostly data objects representing vertexes and edges) are used in a single iteration, which is long enough for them to be promoted into the old genera-
5.6 Application Throughput

We now discuss the throughput obtained for each GC and workload (except for Feedzai). We do not show the throughput for Feedzai’s workload because the benchmark environment (where the Cassandra cluster is used) dynamically adjusts the number of transactions per second according to external factors; e.g., the credit-card transaction generator produces different transactions over time, some per second according to external factors; e.g., the credit-card transaction generator produces different transactions over time, some per second according to external factors; e.g., the credit-card transaction generator produces different transactions over time, some per second according to external factors; e.g., the credit-card transaction generator produces different transactions over time.

Regarding G1 and NG2C, both present similar max heap values.

We envision that the NG2C could be integrated in other JVMs and collectors. Even concurrent collectors such as C4 could take advantage of the ideas described in this work to reduce the amount of object copying within the heap and therefore reduce the application interference, possibly increasing the throughput. We are currently working on integrating the object lifetime estimation directly into the JVM in order to allow dynamic N-Generational pretenurization.

11 Both NG2C and the OLR profiler can be downloaded from github.com/rodrigo-bruno/ng2c

6. Conclusions and Future Work

This paper presents the design and implementation of NG2C, a new HotSpot GC algorithm that avoids copying objects within the heap by aggregating objects with similar lifetime profiles in separate generations. NG2C is built on top of G1, by modifying the way it allocates objects and manages generations. The experimental evaluation shows that it is possible to reduce the object copying done by current collectors (G1 and CMS) by up to 89.2%, resulting in shorter GC pause times. We are able to reduce the worst observable GC pause times in Cassandra by 94.8%, 85% for Lucene, and 96.45% for GraphChi. We also show that despite increasing the complexity of the JVM allocation algorithm, NG2C does not penalize application throughput, the heap usage, and the remembered set update work, when compared to current GC implementations.

We envision that the NG2C could be integrated in other JVMs and collectors. Even concurrent collectors such as C4 could take advantage of the ideas described in this work to reduce the amount of object copying within the heap and therefore reduce the application interference, possibly increasing the throughput. We are currently working on integrating the object lifetime estimation directly into the JVM in order to allow dynamic N-Generational pretenurization.
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