INFO411 Memory Management on Mobile Devices

ISMM 2024 – Memory Management on Mobile Devices

Motivation

- Billions of mobile devices, yet **memory management** is understudied compared to servers/desktops.
- Responsiveness (frame rate), energy (cpu/battery), and memory cost (heap size) are critical to user experience.
- Android Runtime (ART), part of the **Android OS**, is:
 - Open-source
 - Garbage-collected
 - Runs across low- to high-end devices
- ?How do OS garbage collectors behave on real-world mobile apps?



Background - ART Runtime

- Android Runtime (ART):
 - Zygote → forks every app process
 - Both **JIT** and **AOT** compilation available
 - Collectors: SemiSpace, Concurrent Copying, Concurrent Mark-Compact
- OS level GC ≠ app-level GC
 - Impacts all apps sharing the OS
 - Must measure mutator cost + responsiveness

Architecture



Challenges

- Multi-tenancy: Many apps/services share limited OS memory.
- Lack of benchmarks: No standard suite of open-source Android OS apps.
- **Non-determinism**: Network, GPS, UI events → reproducibility issues.
- **Heap size control**: Apps inherit from the OS Zygote → hard to tune per-app.
- Heap introspection loops: Apps adapt to OS memory pressure.
- Closed-source apps: Frequent updates + UI changes → flaky benchmarks.

Framework Design – Key Principles

Heap size control

- Hijacked Zygote fork to enforce per-app heap limits
- First systematic mechanism for OS-level GC evaluation

GC cost attribution

- Extended ART to log GC phases
- Collected perf counters:
 - CPU cycles
 - Task clock
 - Instructions retired 🗹
 - Page faults
- Also measured wall-clock time, but discarded as too noisy

· Responsiveness metrics

- Measured frame jank & render times via gfxinfo
- User-visible latency, not just GC pause times
- Percentiles (P50, P99, P99.9) for frame times to capture stutter

Framework Design - Pipeline

App → Modified ART → Mock APIs → UI Automator → Metrics

- Controlled heap configuration at fork
- Mocked heap introspection APIs → stable values
- Automated user events via UI Automator
- Logged GC timings + frame stability

Framework Design - Challenges Addressed

Heap introspection feedback loops

- · Maps, Instagram adapt to "available memory"
- · Solution: Fake responses via modified ART

Non-determinism

- Cached TikTok feeds & fixed content
- Forced AOT compilation → steady state

· Idempotent benchmarks

Cold-start every run

• Fixed app versions, reproducible UI scripts

Whitebox approach for analysis

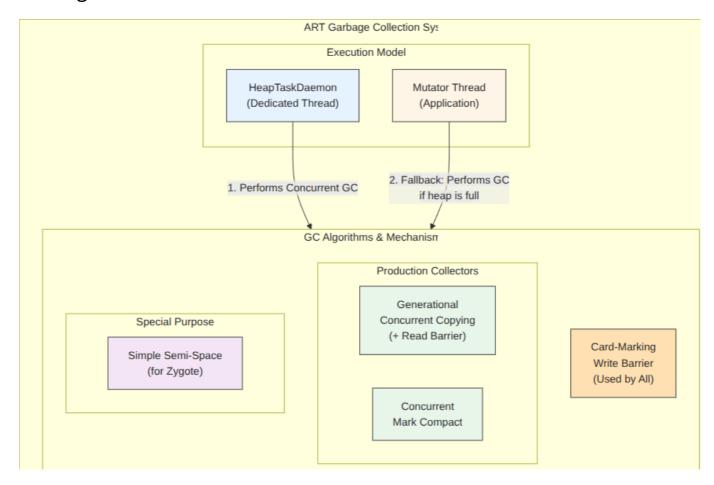
• **Heap size control**: via Zygote hijack

• **Heap introspection**: ART returns fake values → prevent feedback loops

• Network variability: Pre-cached data, curated feeds

Compilation noise: Forced AOTApp state: Cold-start enforced

Garbage Collection



Cleaners (Collectors)

- Generational Concurrent Copying Cleaner 🙆
 - "Quick tidy-up kid"
 - Frequent, lightweight cleanups
 - Write barrier + read barrier ensure safety

Cleaners (Collectors)

- Concurrent Mark-Compact Cleaner @
 - "Deep-cleaning parent"

- Less frequent, re-organizes heap
- More space-efficient for long-lived workloads

Benchmarks - Design

- · Vanilla Java benchmarks
 - DaCapo subset, GCBench
 - Controlled, stable workloads
- · Real-world apps
 - Gmail, TikTok, Instagram, Maps, Acrobat, Airbnb
 - Represent actual OS-level stressors
- Excluded: browsers & games (too dynamic, non-reproducible)

Evaluation Framework

- Modified ART to:
 - Control heap per-app (Zygote fork)
 - Mock heap APIs (break feedback loops)
 - Automate UI input sequences
- ?Can OS-level collectors be measured fairly for both mutator cost and responsiveness?

Evaluation - Methodology

- Devices: Pixel 7 Pro (12 GB), Pixel 4a 5G (6 GB)
- · Controls:
 - Disabled SIM/Bluetooth/location
 - Fixed CPU frequency, pinned cores
 - Forced AOT warmup
- · Lower Bound Overhead (LBO):
 - SemiSpace/NoGC as baselines
 - Reported results = empirical *lower bounds* on GC cost
- ☼ CPU cycles reported slightly higher overhead than task clock → apps did extra work, not just slowing

Evaluation - Vanilla Java Workloads

- Optimized SemiSpace: lowest mutator overheads (14–27%)
- Concurrent Copying (CC): 10–23%, cache-friendly at small heaps
- Concurrent Mark-Compact (CMC): 11–32%, more space-efficient
- Takeaway: No single collector dominates

- Overheads: 2% 51%, strongly app + heap dependent
- Trends:
 - SemiSpace (optimized) → best for mutator overhead
 - CMC → better for tight heaps (e.g., Maps)
 - Pause times ≠ responsiveness

Evaluation – Responsiveness

- Frame distributions (Gmail, Acrobat)
 - P50, P99, P99.9 → smoothness vs jank
 - 99.9th percentile → **stutter** despite short pause times
- Insight: Must use frame stability metrics, not just stop-the-world pauses
- Different apps show unique GC sensitivity patterns

Evaluation – Anomalies

- **Twitter/X:** highly unstable → discarded from results
- Google Maps: minimum heap size changed daily with updates
- ! Highlights difficulty of reproducibility with closed-source apps

Evaluation - Experimental Device

Pixel 7 Pro

Component	Specification	
	2× Cortex-X1 @2.85GHz	
CPU	2× Cortex-A78 @2.35GHz	
	4× Cortex-A55 @1.8GHz	
Memory	12 GB LPDDR5	

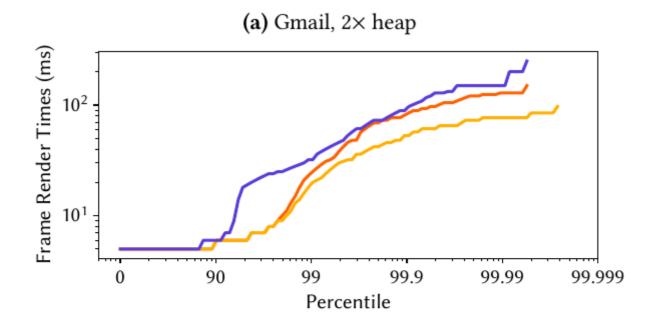
Evaluation - Heap Sizes (Apps)

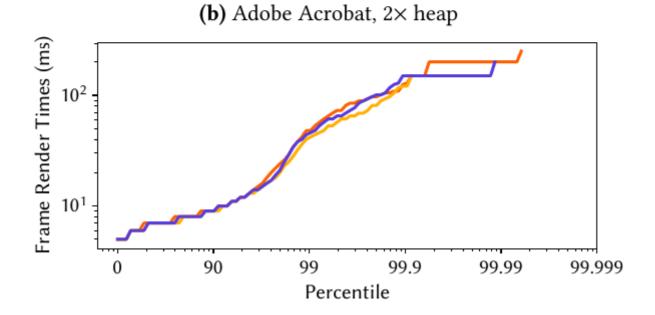
Minimum Heap Sizes (MB)

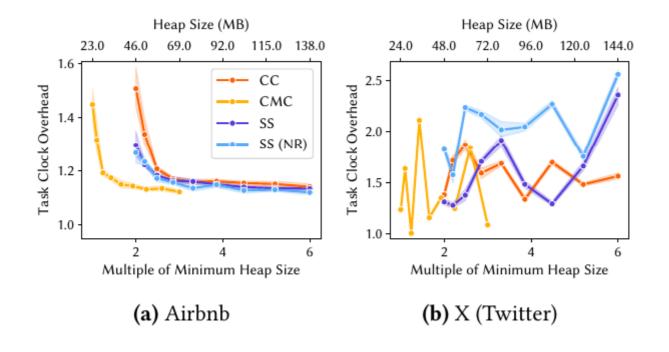
Benchmark	Pixel 7 Pro	Pixel 4a 5G
Acrobat	18	18
Airbnb	23	23
Discord	19	19
Gmail	14	14
Google News	14	17
Maps	65	65

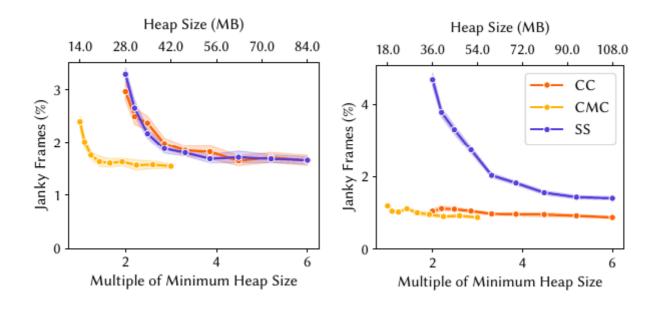
Evaluation - Key Results

- OS-level GC overheads: 2% → 51%
- SemiSpace (optimized): best mutator overhead
- CMC: most space-efficient
- Responsiveness metrics:
 - Pause times ≠ user experience
 - Frame stability (percentiles) = better predictor
- Geometric mean overheads and LBO tables used for fair comparisons









Discussion - Time vs Space Tradeoff

- SemiSpace: low mutator cost, but higher heap demand
- CMC: space-efficient, but overhead increases with workload
- Concurrent Copying: good balance for smaller heaps
- X No universal best GC across workloads

Discussion - What Surprised Us

- SemiSpace often outperformed concurrent collectors
- Pause time metrics failed as predictors of responsiveness
- · Closed-source app volatility (heap growth, updates) complicates research

• Demonstrates need for robust open benchmarks

Summary Takeaways

- **Example 2** Framework: First systematic GC evaluation for Android
- LLL Evaluation: Benchmarks across real apps + Java workloads
- the **Tradeoffs:** SemiSpace → lowest overhead; CMC → most space-efficient
- @ Responsiveness: Frame stability (P50/P99/P99.9) > pause times

Future Improvements

- Build open-source benchmark suite for reproducibility
- Stronger solutions to heap introspection loops
- Improve reproducibility under dynamic events
- Extend framework to other mobile OSes
- Explore collectors optimizing time-space tradeoffs for small heaps

?What OS GC designs can sustain performance across all tiers of devices?



Broader Impact

- Provides first reproducible framework for GC research on Android
- Helps academia & industry evaluate collectors under realistic mobile workloads
- Paves way for **next-gen collectors** balancing mutator cost, responsiveness, and space efficiency