DATA+AI SUMMIT EUROPE
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TeraCache: Efficient Caching over Fast Storage Devices

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Spark Caching Mechanism

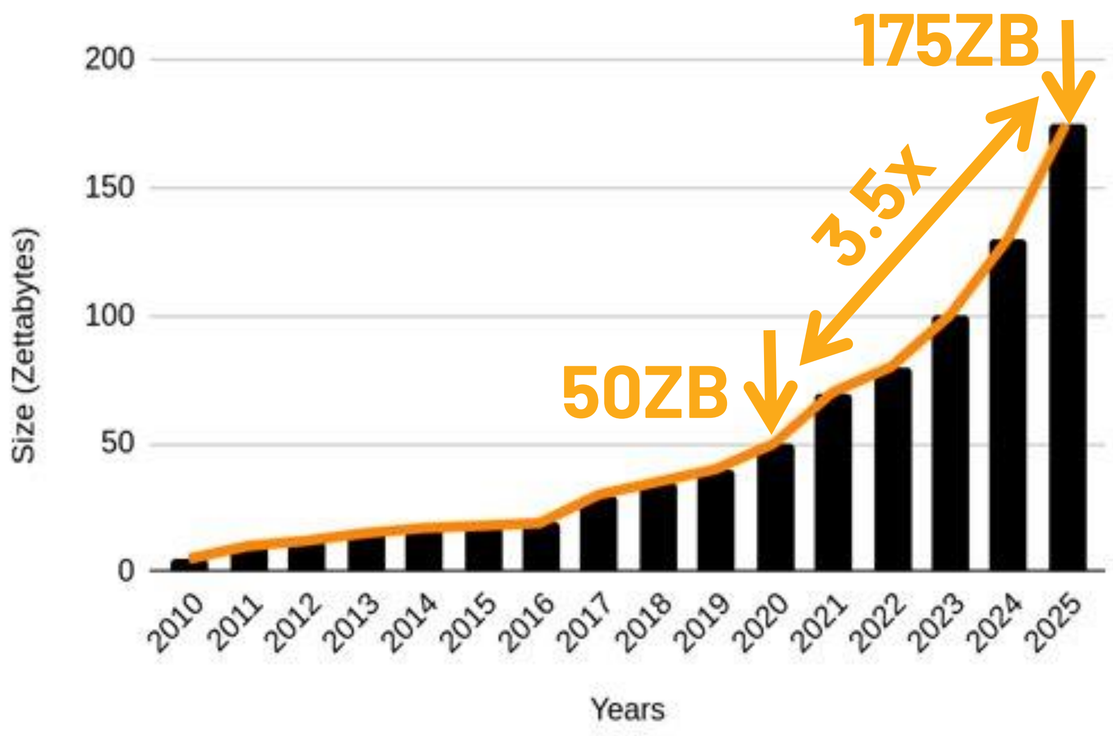
- Stores the result of an RDD
- Essential when an RDD is used across multiple Spark jobs
- Caching avoids recomputation and reduces execution time
- Effective for iterative workloads (e.g., ML, graph processing)
- How much data do we need to cache?

Storage Level
MEMORY_ONLY
MEMORY_AND_DISK
DISK_ONLY
OFF_HEAP

Source: https://spark.apache.org/docs/latest/rdd-programming-guide.html

Increasing Memory Demands!

- Analytics datasets grow at high rate
  - Today ~50ZB
  - By 2025 ~175ZB
- Typical deployments use roughly as much DRAM as the input dataset
- Typically cached data is even larger than the input dataset



Source: Seagate – The Digitization of the World

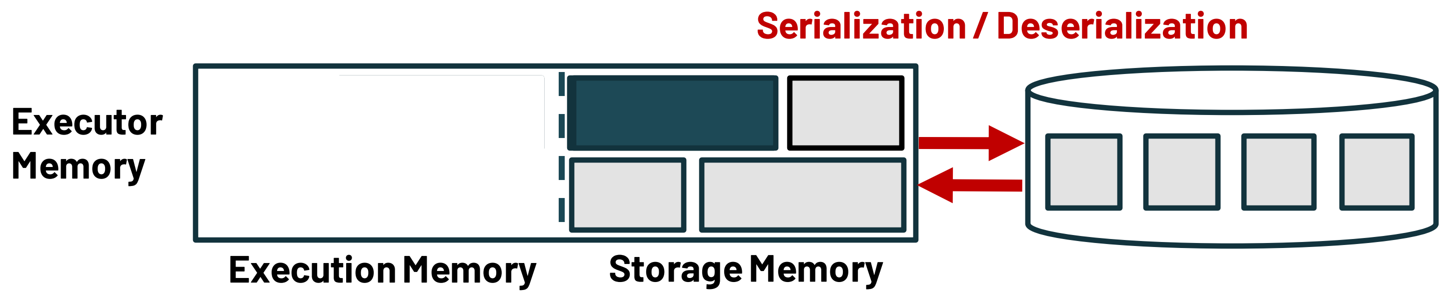
Cached Data Size Matters

- In-memory caching needs a lot of DRAM
- DRAM density difficult to increase
- Fast storage (NVMe) scales to TBs/device
- Spark already uses **fast storage** for cached data – However, at **high cost**

3x

Workload	Input Dataset (GB)	Cached Rdds (GB)
Linear Regression (LR)	64	182
Log. Regression (LgR)		160
SVM		188

Dilemma: On-heap vs Off-heap NVMe Caching

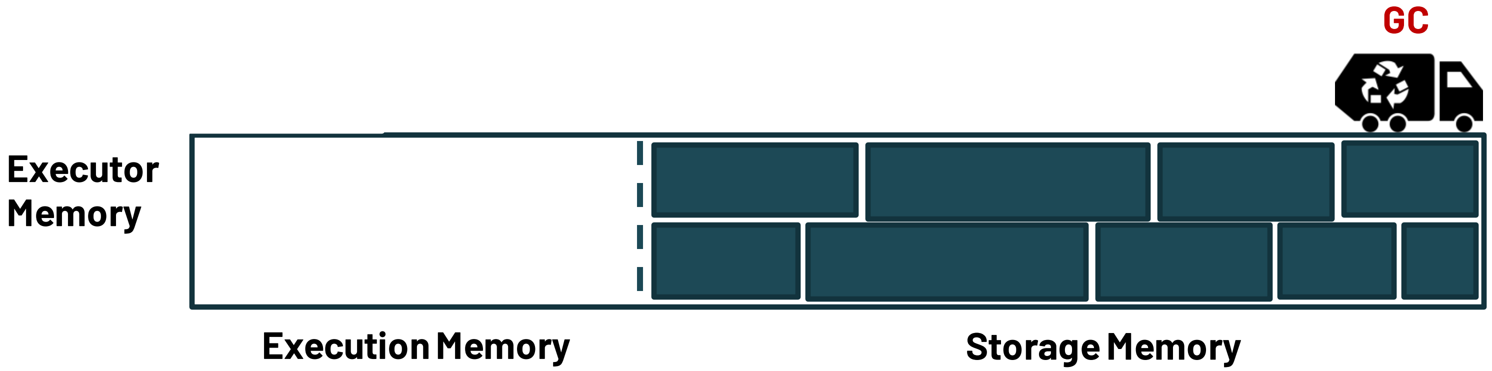


Serialization / Deserialization

Executor Memory

Execution Memory

Storage Memory



GC

Executor Memory

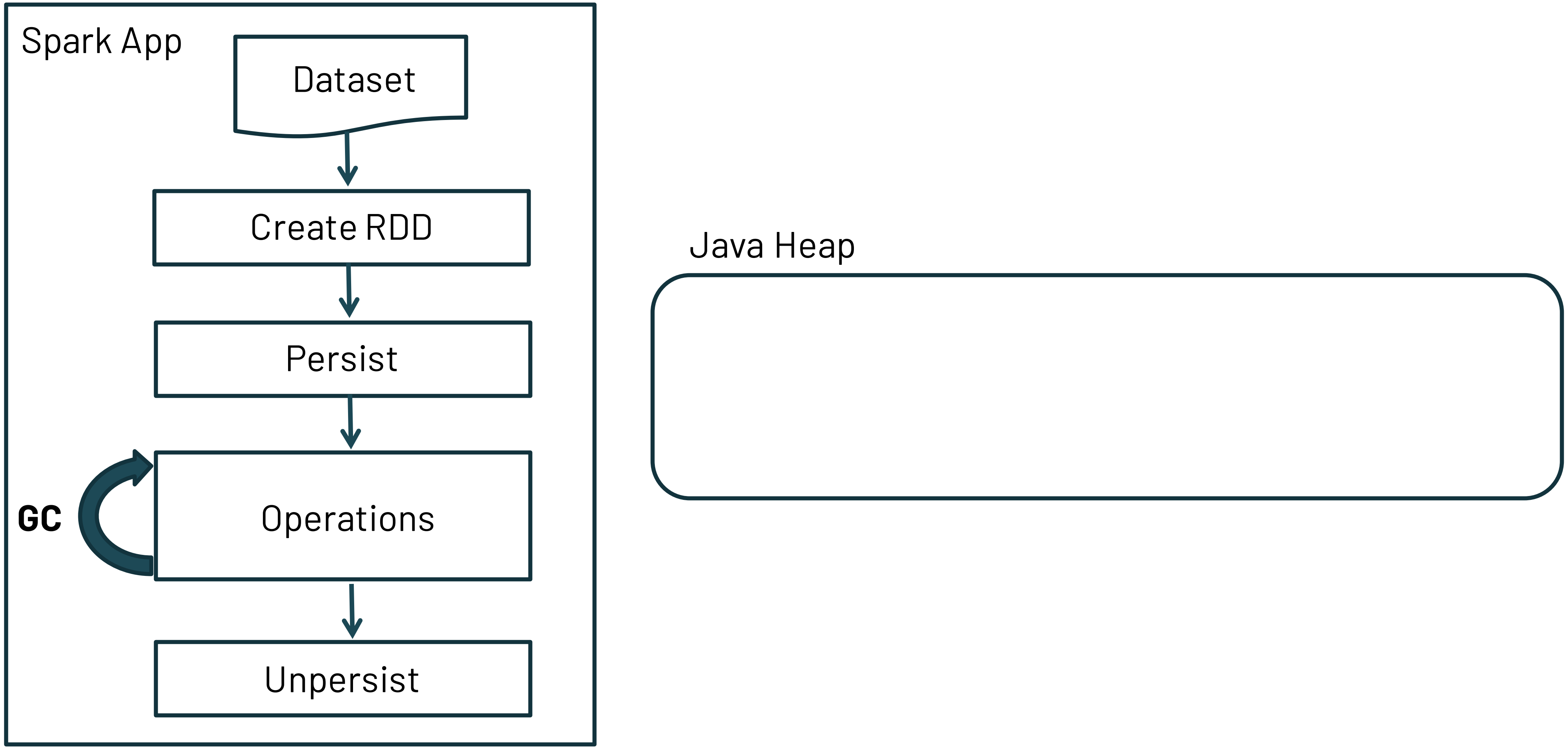
Execution Memory

Storage Memory

	Pros	Cons
On-heap Cache	No Serialization	High GC
Off-heap Cache	Low GC	High Serialization

Can we avoid Serialization and reduce GC?

Cached Objects Behave Differently



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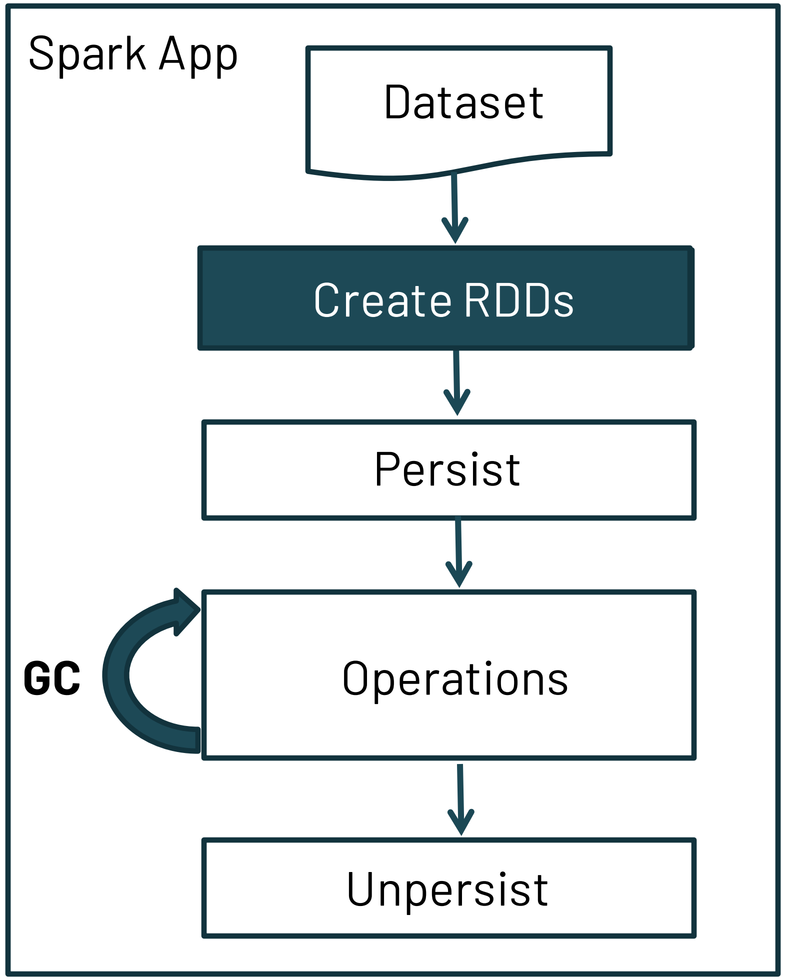


Spark App

Dataset

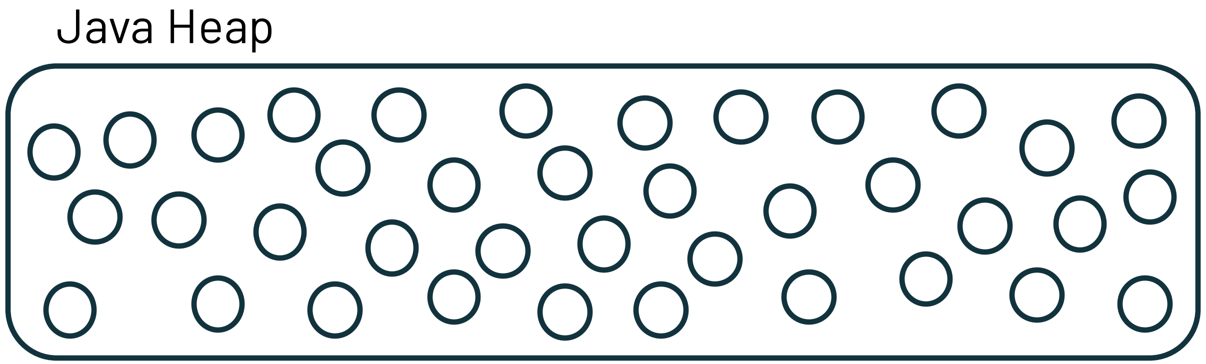
Create RDDs

Persist

Operations

Unpersist

GC



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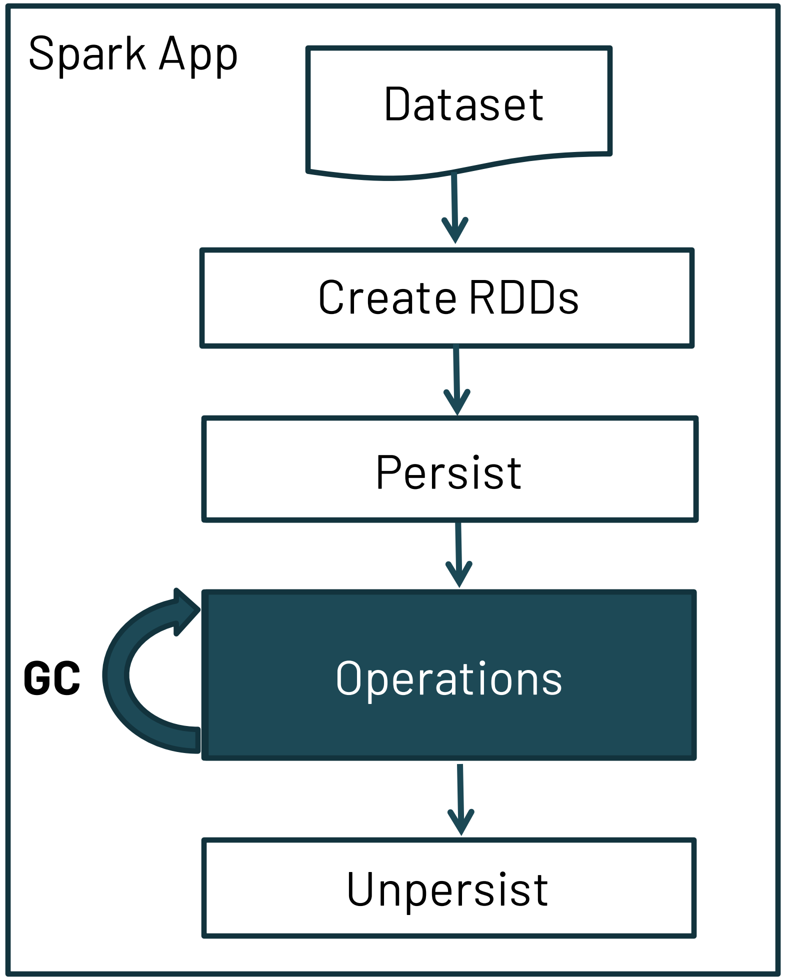
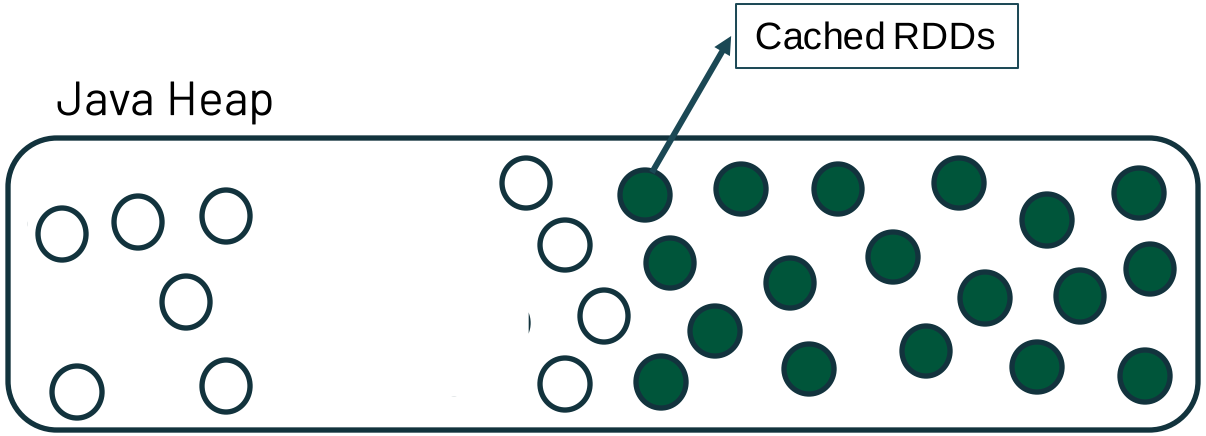
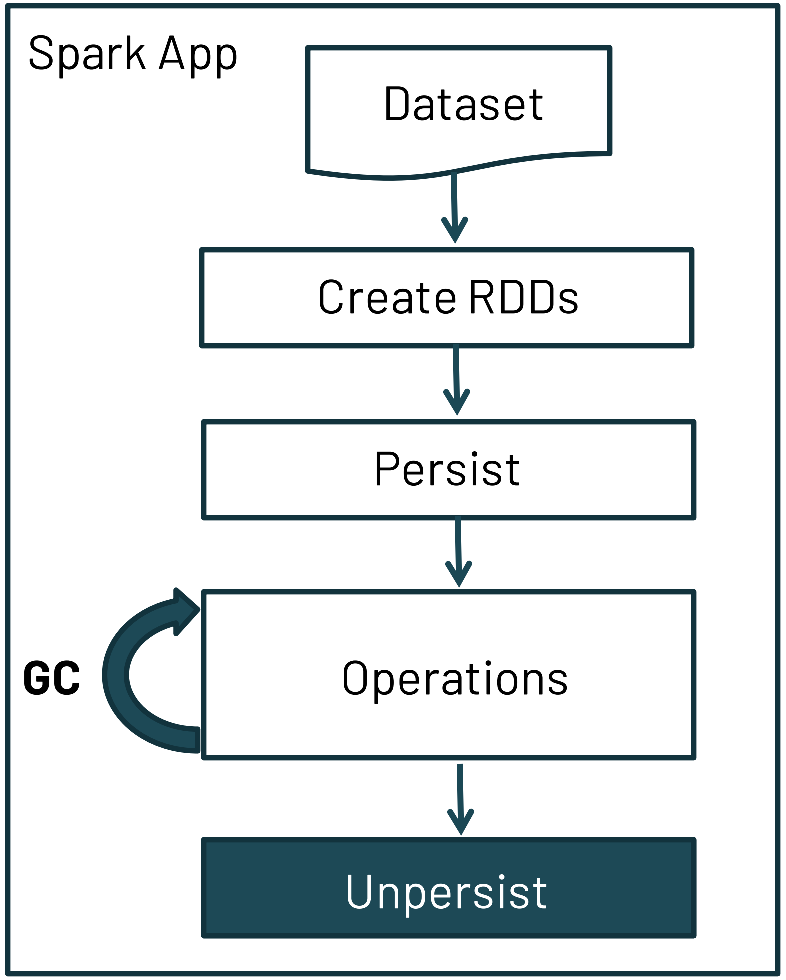
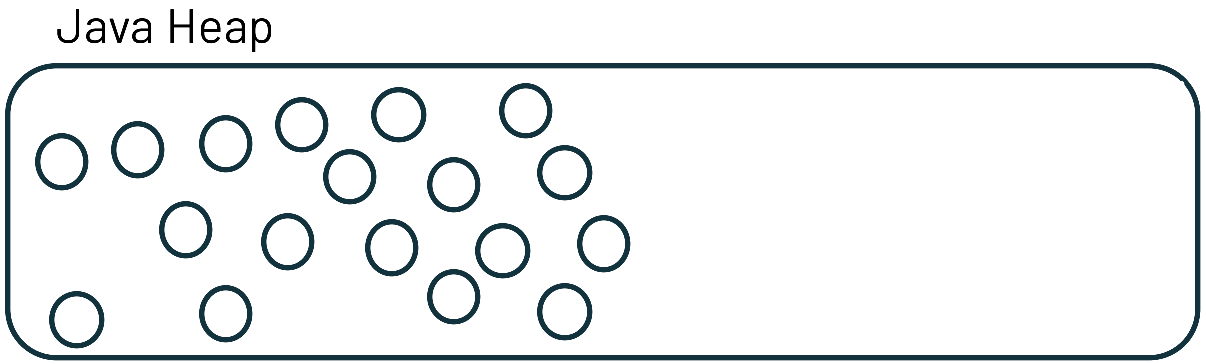




- GC between **persist-unpersist** extremely wasteful
- GC scans all objects in the heap

Cached Objects Behave Differently





- GC reclaim cached RDDs after unpersist

Our Approach: Treat Cached Objects Differently

- Objects in JAVA **follow** generational hypothesis
- Opportunity: **Nomadic hypothesis observation**
- Spark cached objects are
  - Long-lived: Used across multiple Spark jobs (**cache**)
  - Intermittently-accessed: Long intervals without access (**NVMe**)
  - Grouped life-times: RDD objects leave the cache at the same time (**unpersist**)
- **Place cached objects in a special heap**

TeraCache: Introduce a Second JVM heap on NVMe

- Execution Heap remains as a garbage collected heap
  - Maintains the JVM heap for execution purposes

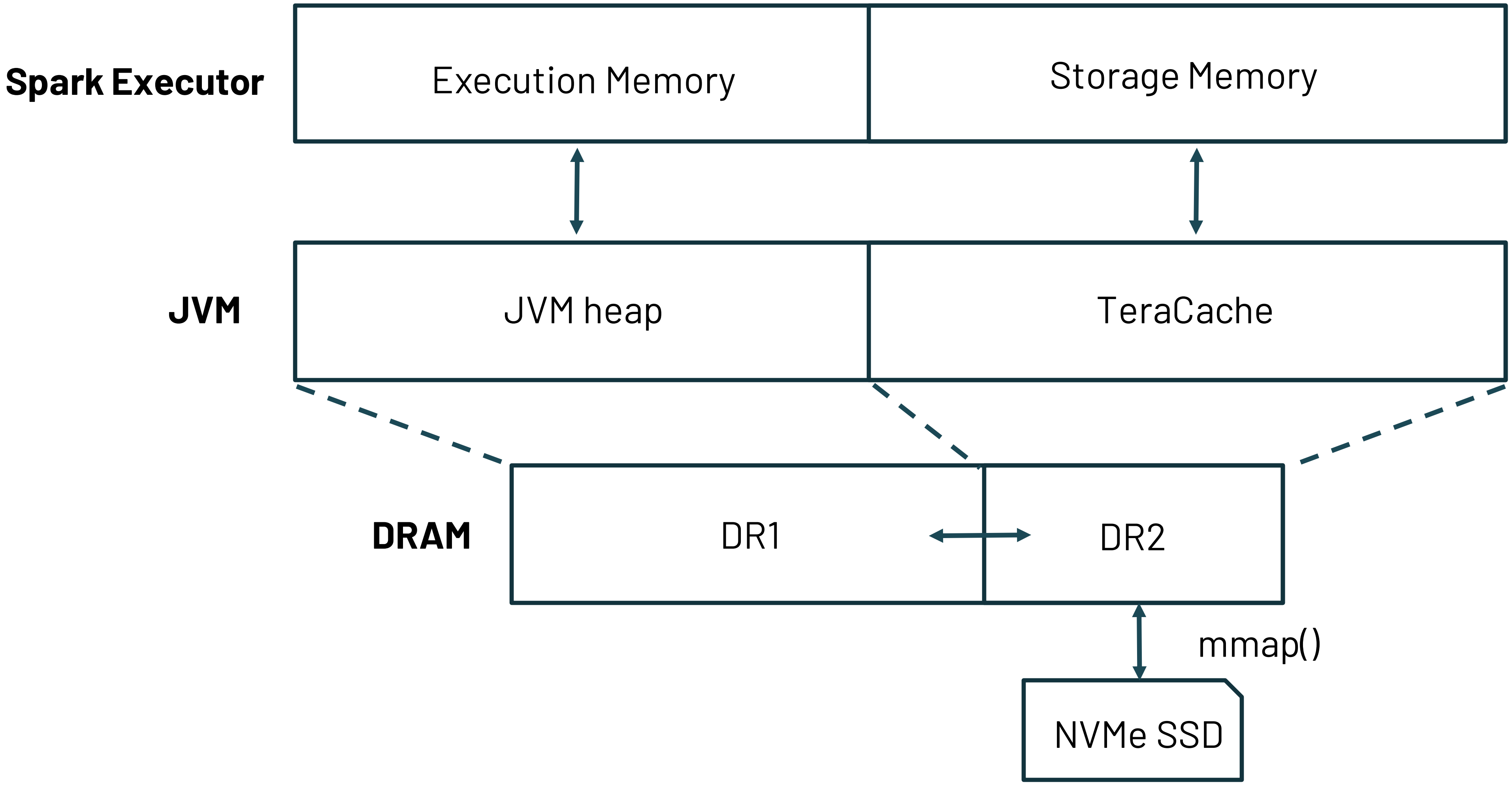
- The **second TeraCache heap** has two significant advantages

- **No GC:** Use persist/unpersist semantics to avoid GC

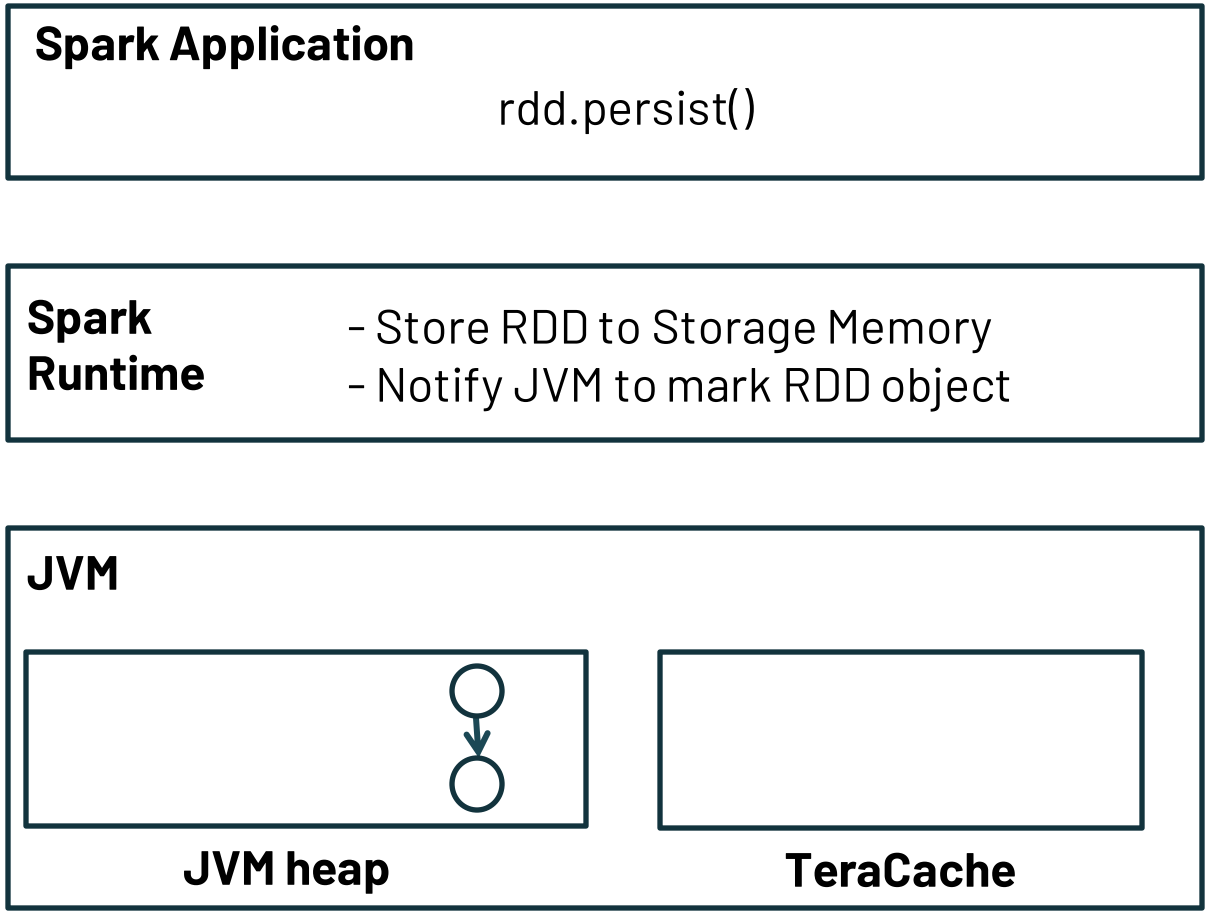
- **No Serialization/Deserialization:** Use memory-mapped I/O

TeraCache Design Overview

TeraCache: Design Overview



Spark Knocks on the JVM Door



Spark Application

rdd.persist()

Spark Runtime

- Store RDD to Storage Memory
- Notify JVM to mark RDD object

JVM

JVM heap

TeraCache

- Spark notifies JVM for RDD caching
    - At persist/unpersist operations
- Add new TeraFlag word in JVM objects
- JVM creates new object, sets TeraFlag

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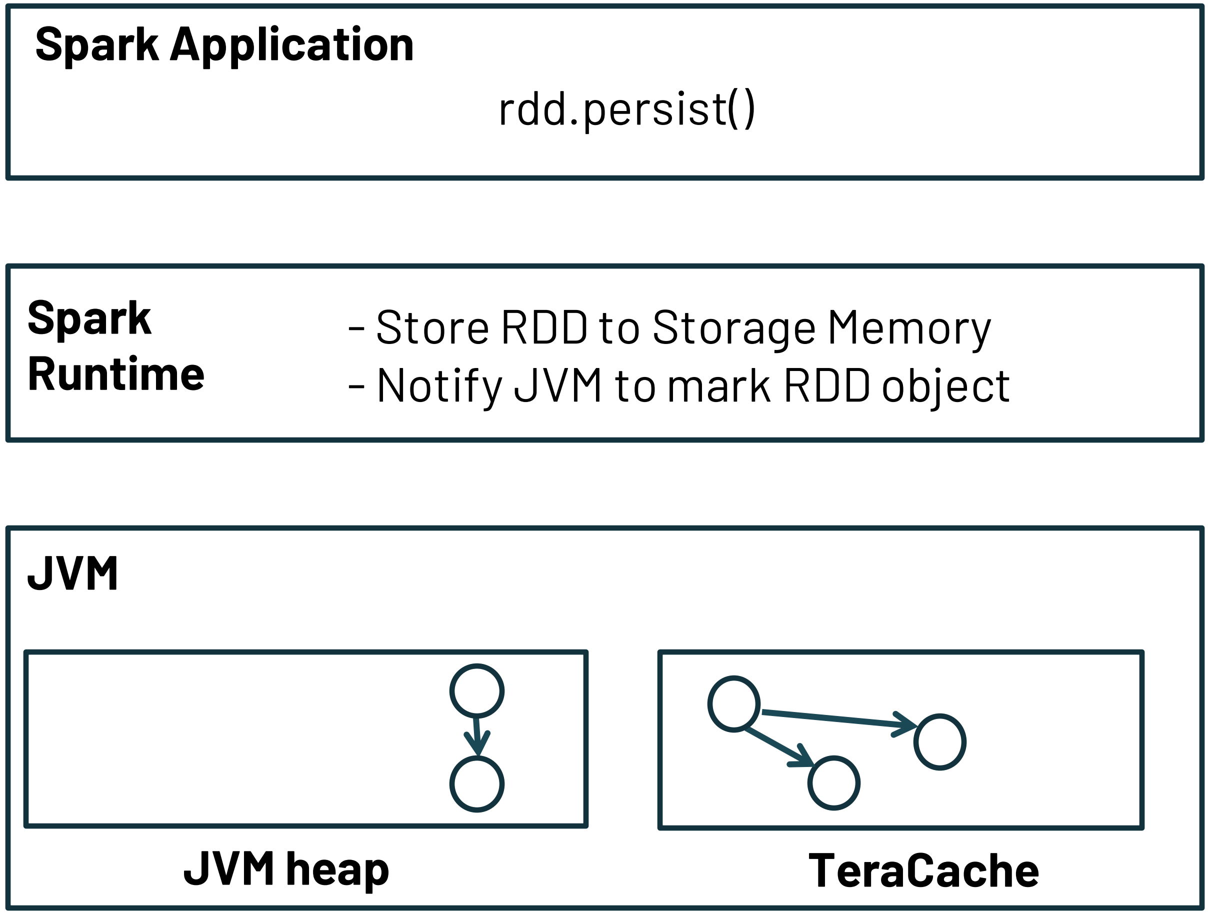

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TeraCache

- Spark notifies JVM for RDD caching
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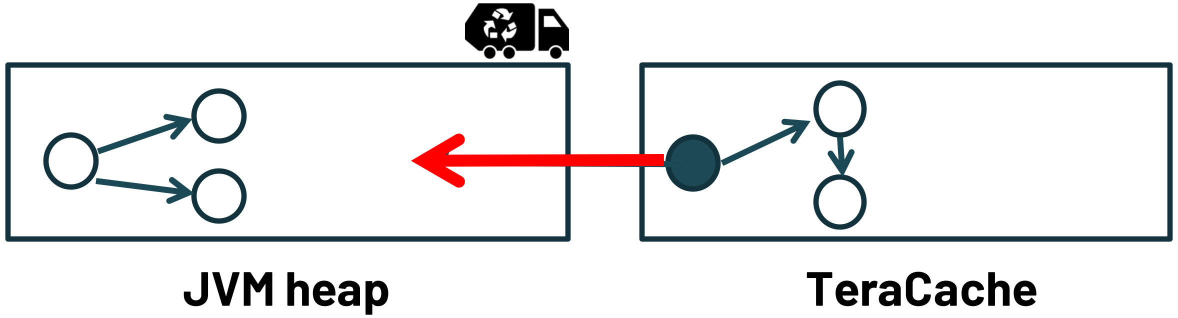
- Add new TeraFlag word in JVM objects
- JVM creates new object, sets TeraFlag
- Move to TeraCache during next full GC

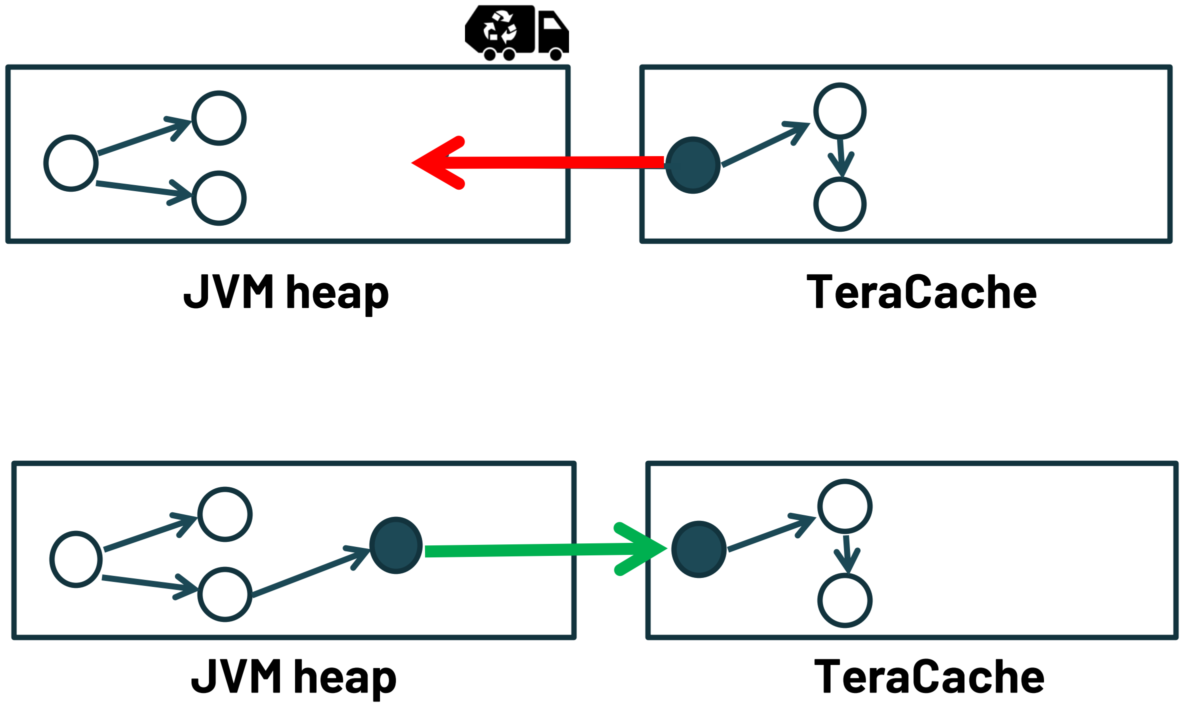
TeraCache Design: Avoid GC

How to Avoid GC in TeraCache?



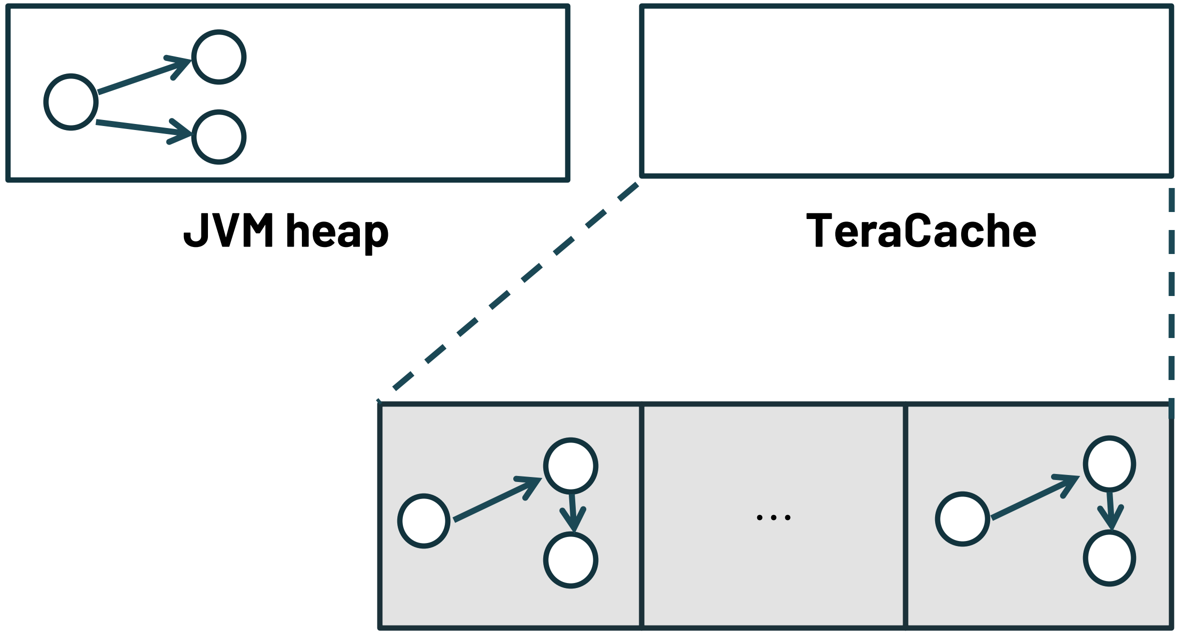
- **Disallow** backward pointers to Heap
- Move **transitive closure** in TeraCache

How To Avoid GC in TeraCache?



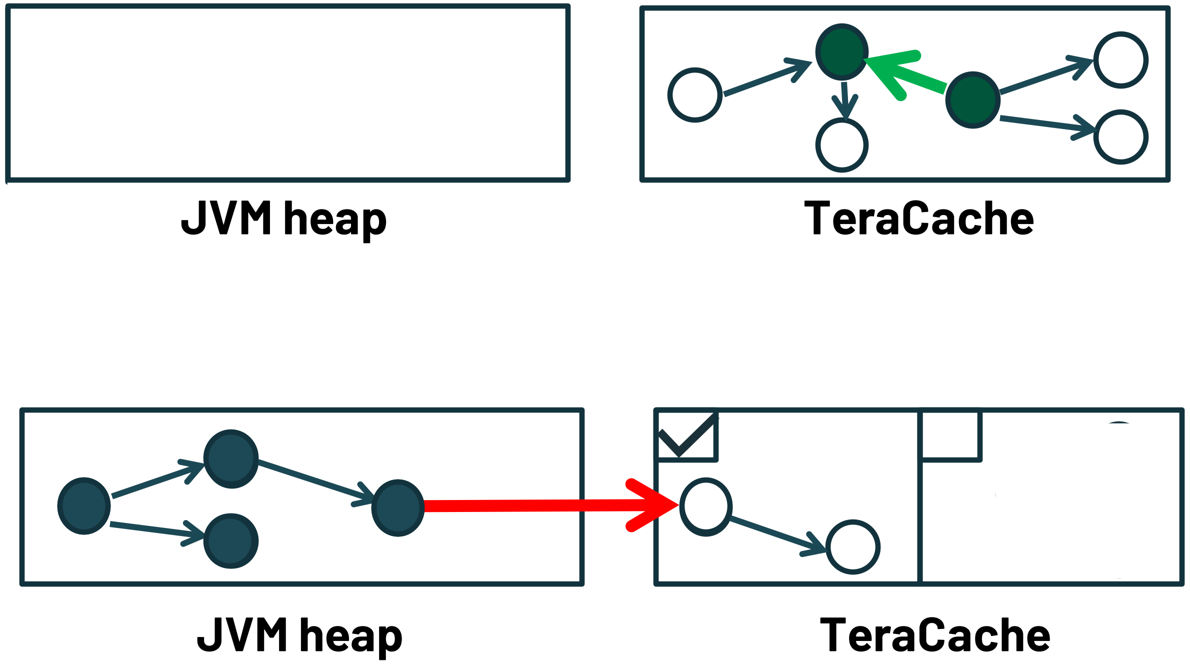
- **Disallow** backward pointers to Heap
- Move **transitive closure** in TeraCache
- **Allow** forward pointers from Heap
- Objects in TeraCache **do not move**
- **Fence GC** from following forward pointers

Organize TeraCache in Regions



- Objects **that belong to the same RDD** have similar life-time
- Organize TeraCache in regions
  - Place objects in regions based on life-time
  - Dynamic size of regions
- Bulk free
  - Reclaim entire region

Bulk Free Regions



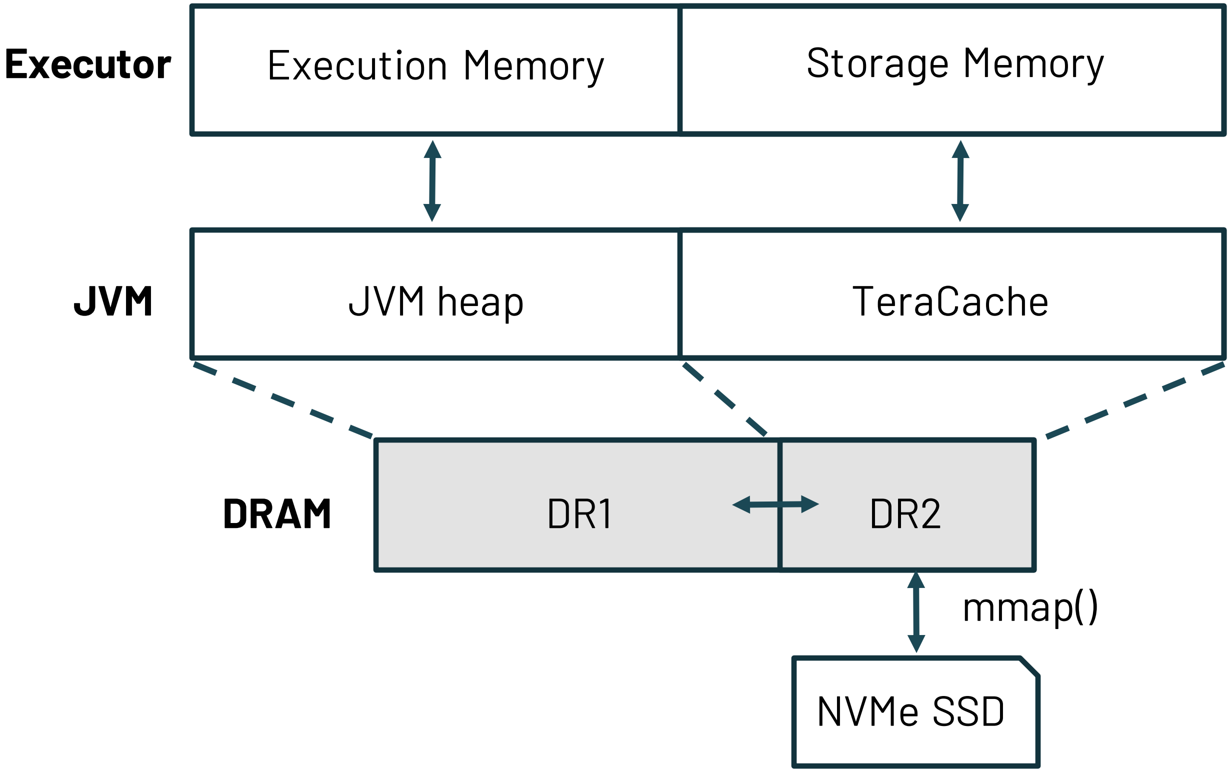
- To provide **correct** and **bulk** free
  - **Allow only** pointers within regions
  - Merge regions with crossing pointers when objects move to TeraCache
- Keep a bit map with live regions
  - Track reachable regions from JVM heap in every GC
- During GC marking phase identify active regions
  - Mark the bit array if there is a pointer from the JVM heap to a TeraCache region

TeraCache Design: Avoid Serialization

No Serialization⟶Memory Mapped I/O

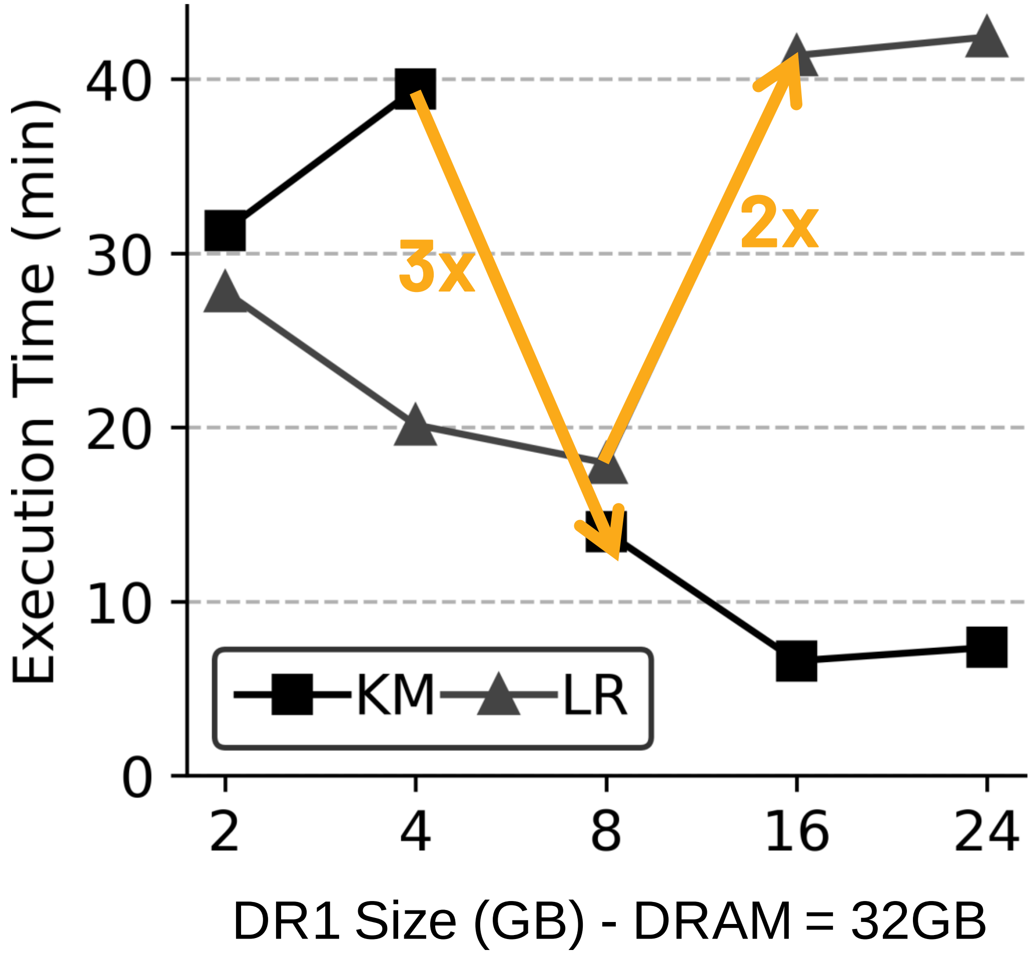
- MMIO allows **same data format** on memory and device
- No explicit device I/O - Only accesses using load/store
- Linux Kernel already supports required mechanisms for MMIO
- We use FastMap [USENIX ATC'20]: Optimize scalability of Linux MMIO

Competition for DRAM Resource



- Execution Memory must reside in DRAM
  - A lot of short-lived data
  - We need large DR1
- Cached objects are accessed as well
  - E.g., Iterative jobs reuse cached data
  - We need large DR2
- Can we statically divide DRAM between the heaps?

Dividing DRAM between Heaps



- KMeans (KM)-jobs produce more short-lived data
  - More minor GCs
  - More space for DR1
- Linear Regression (LR)-jobs reuse more cached data
  - More page faults/s
  - More space for DR2
- Dynamic Resizing of DR1, DR2
  - Based on page-fault rate in MMIO
  - Based on minor GCs

Preliminary Evaluation

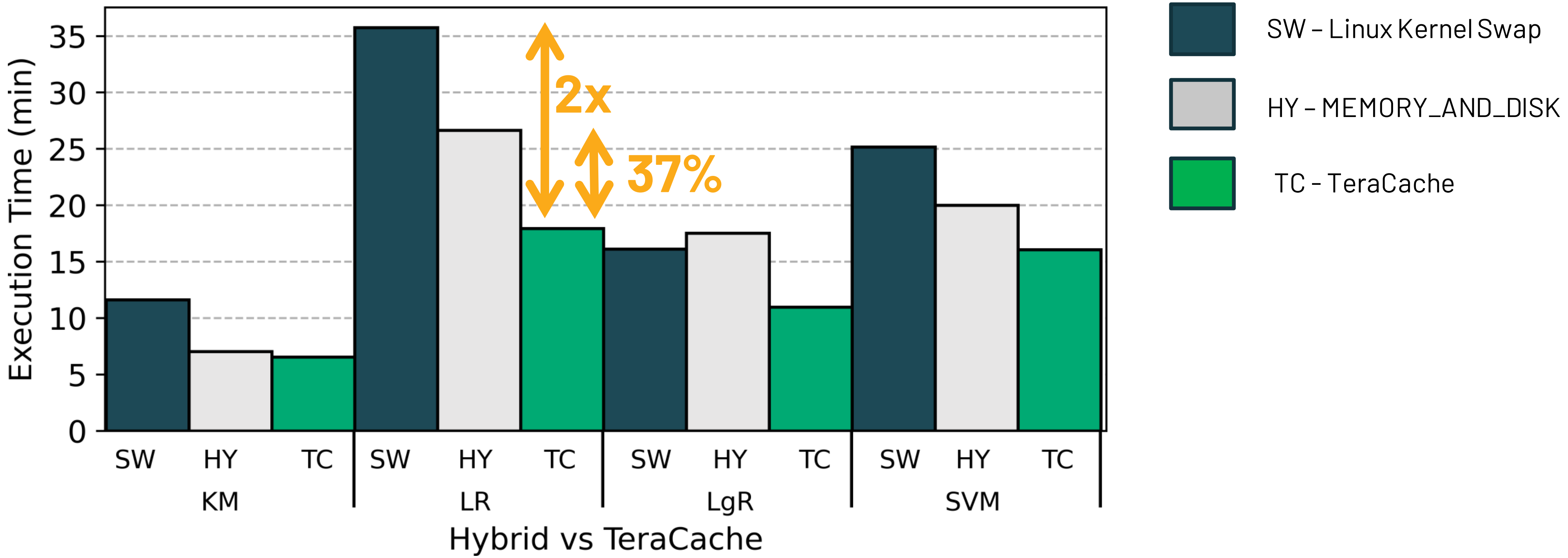
Early Prototype Implementation

- We implement a prototype of TeraCache based on ParallelGC
  - Place New Generation on DRAM
  - Place Old Generation on fast storage device
  - Explicitly disable GC on Old Generation

- Remaining to be implemented
  - Cached RDDs reclamation
  - Dynamic DR1/DR2 resizing

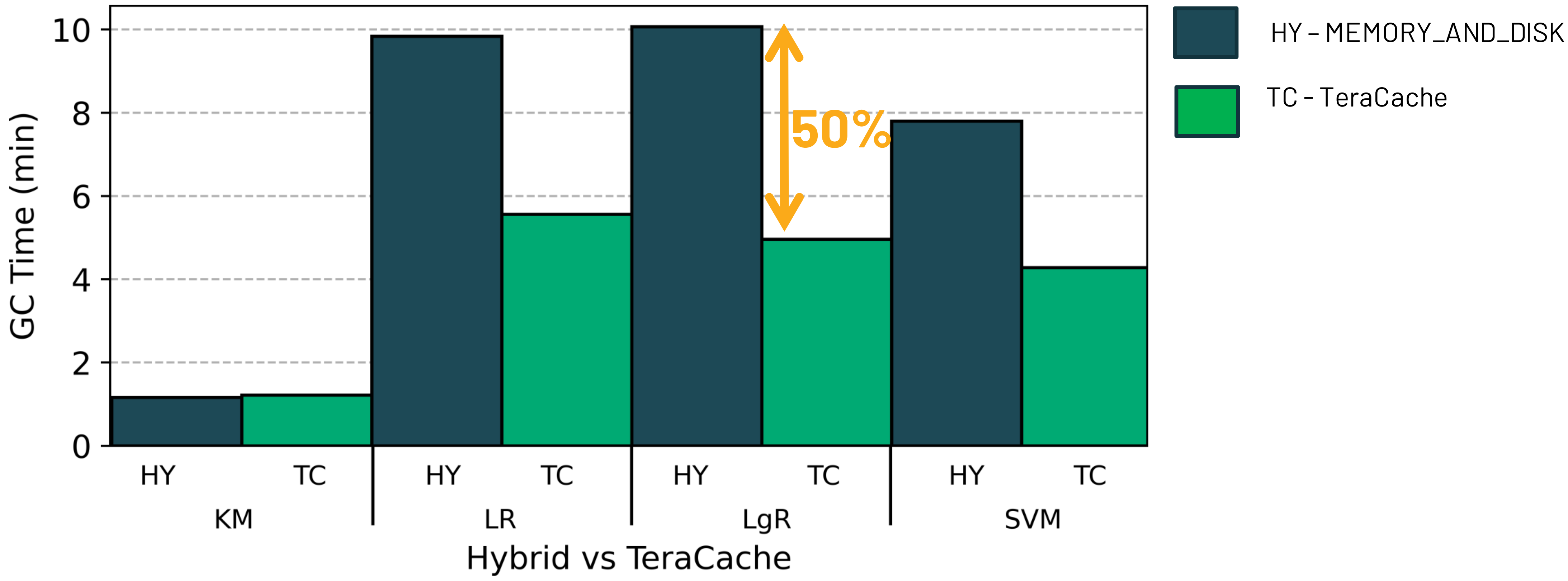
- Evaluation
  - GC overhead
  - Serialization overhead

TeraCache Improves Performance by 25%



- Compared to Serialization: **TC better up to 37%** (on average 25%)
- Compared to GC + Linux swap: **TC better up to 2x**

TeraCache Reduces GC Time by up to 50%



Conclusions

TeraCache: Efficient Caching over Fast Storage

- Spark incurs high overhead for caching RDDs
- We observe: Spark cached data follow a **nomadic hypothesis**
- We introduce TeraCache which both reduces GC and eliminates serialization by using two heaps (**generational, nomadic**)
- We improve performance of Spark ML workloads by 25% (avg)
- Currently we are working on the full prototype

Thank you for your attention

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