TeraCache: Efficient Caching over Fast Storage Devices

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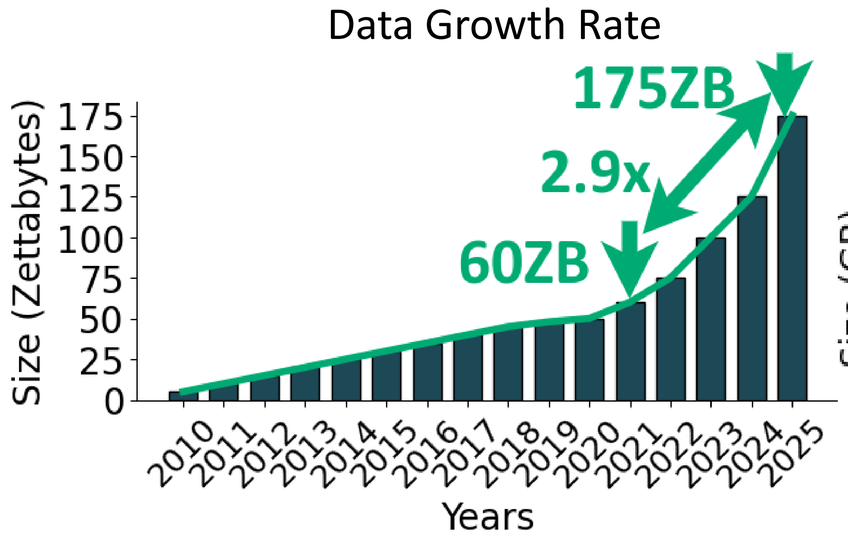
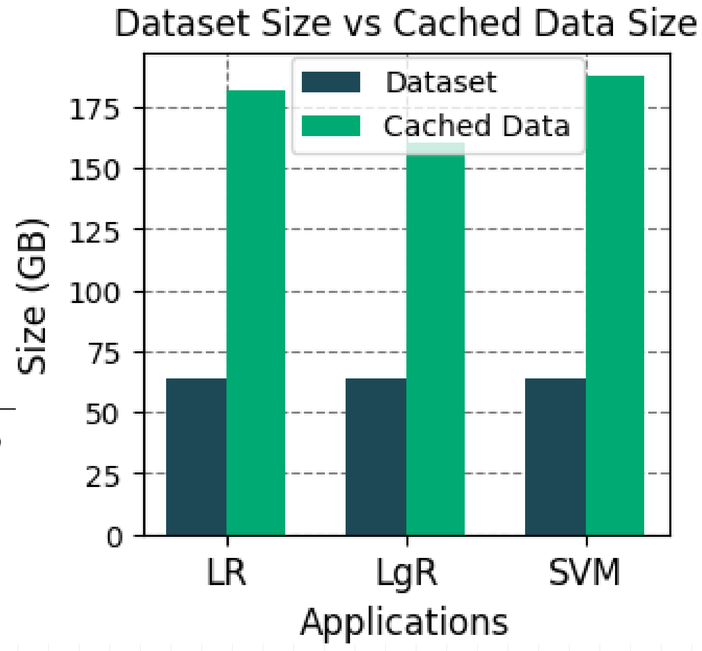
Fast Storage Devices Available but Analytic Stacks Not Ready

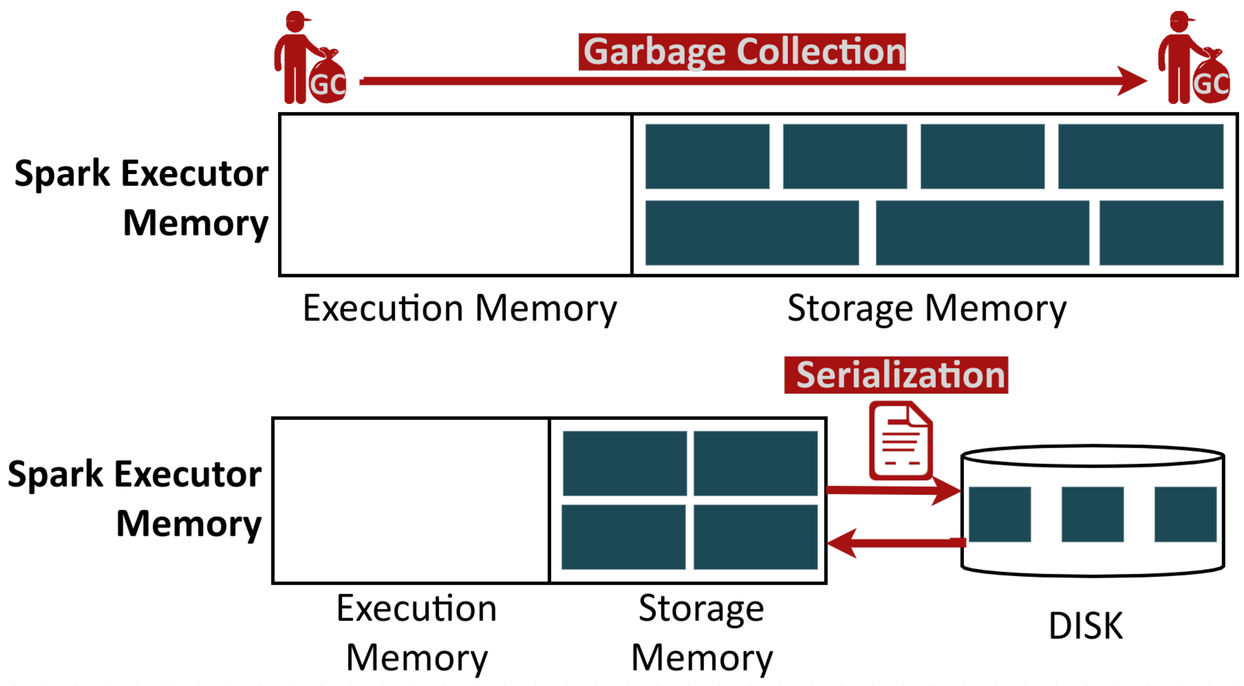
Increasing Memory Demands for Analytics

- Analytic servers use caches for avoiding recomputation (compute caches)
- Cache size is often several times the input dataset size
- DRAM scaling is limited (more $ per GB)
- Analytics resort to high capacity, fast storage devices, such as NVMe



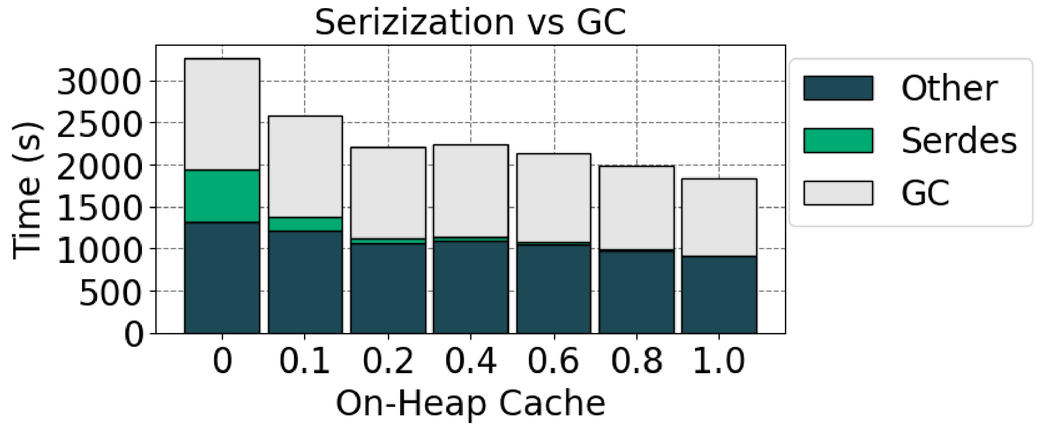


Spark Offers On-Heap and Off-Heap Caching



Merging On-Heap and Off-Heap Benefits

[HTML]D6D6D6	Pros	Cons
[HTML]D6D6D6**On-heap**	No Serialization	High GC Time
[HTML]D6D6D6**Off-heap**	Low GC Time	High Serialization

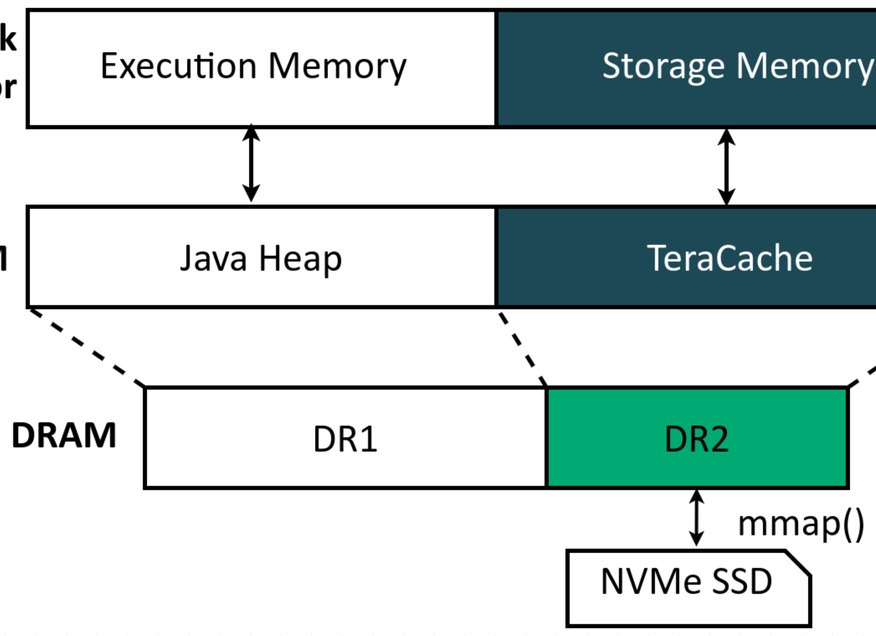


TeraCache: Best of Both Worlds!

Java Heap is garbage collected

Java Heap is fully located on DRAM (DR1)

DR2 hosts memory mappings for TeraCache



TeraCache is non garbage collected

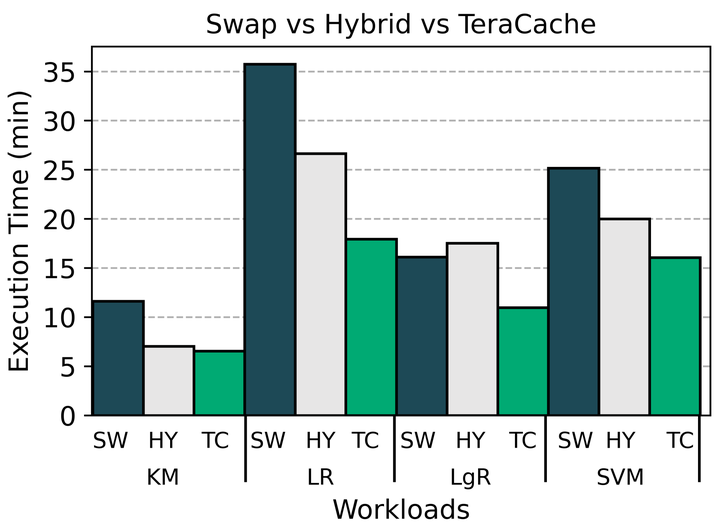
Spark informs JVM for cached data objects

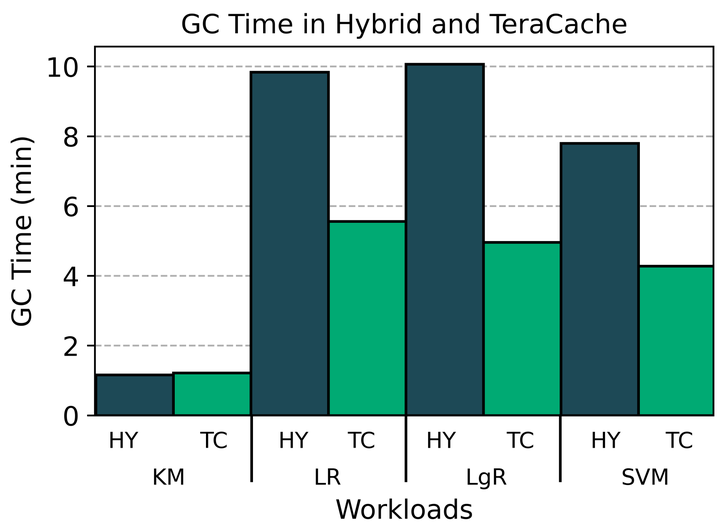
Use of memory-mapped I/O to access the storage device

Challenges

- Interaction between Spark and JVM
- Keep classes loaded
- Keep reachable objects from TeraCache alive
- Extend post write barriers
- Extend Interpreter and JIT to support updates in TeraCache

Machine Learning Workloads





Key Takeaways

- RDD caching is critical in Spark
- GC and serialization introduce significant overhead
- TeraCache improves ML workloads performance by 25% over the state-of-the-art