# Compaction management in distributed key-value datastores

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# **Bettina Kemme**

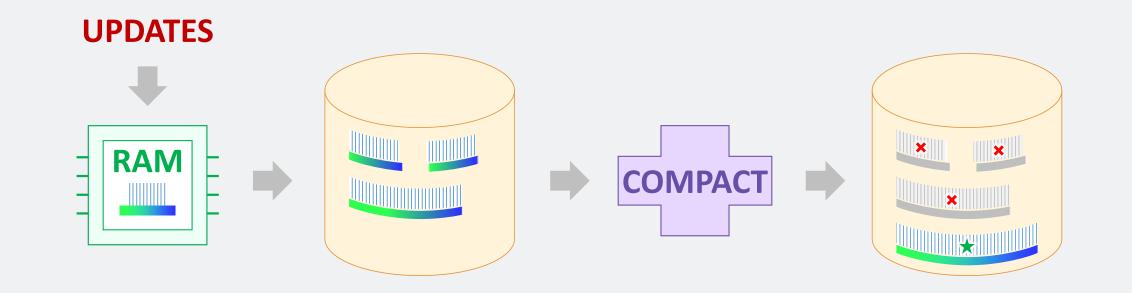
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# COMPACTIONS

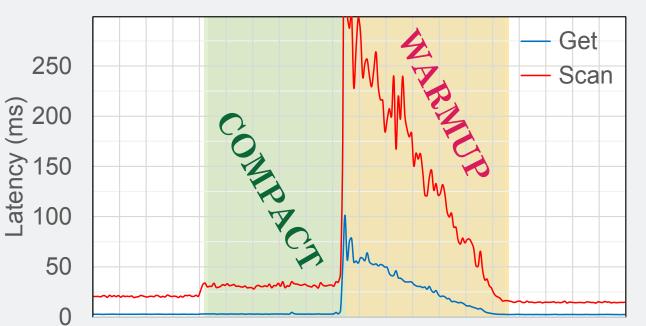
Periodic data maintenance for multi-version stores

Consolidate updates into existing dataset



#### **EXPERIMENTS**

- YCSB update workload triggers compactions.
- YCSB read worklaod
   measures get/scan latency.
- 1x region server (RS),



Prevent read latency from degrading over time

- Reduce number of overlapping data files to be read

#### **Compactions are expensive!**

- 1. **During** execution: compete with workload for resources
- 2. After execution: degrade read latency severely
  - Input files removed, evicted en masse from cache

► Cache misses

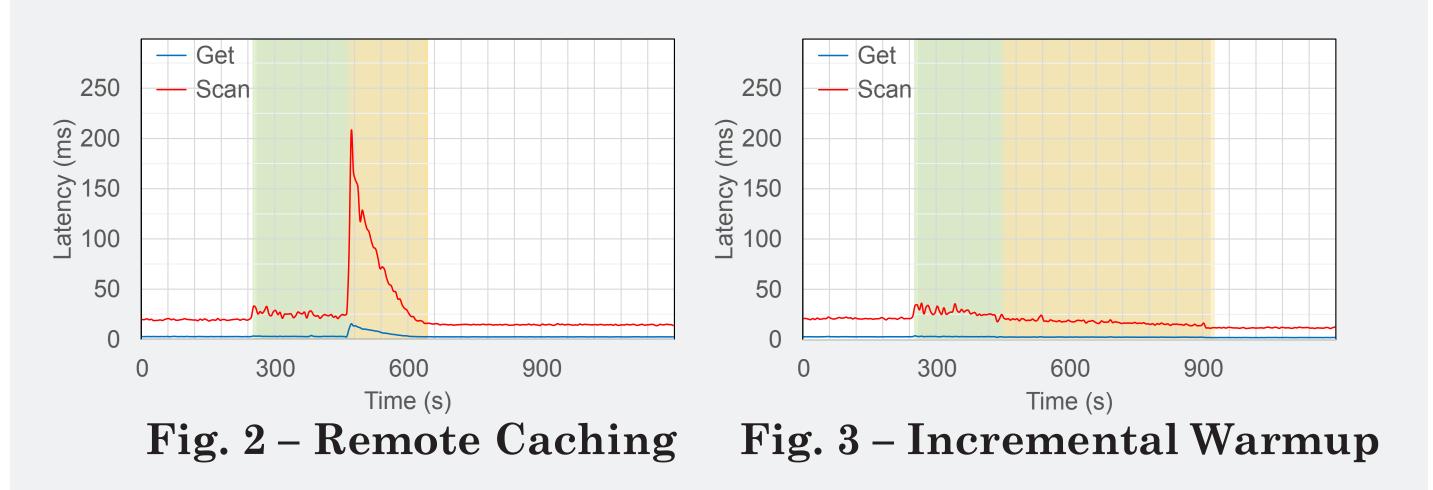
GOALS 1. Reduce compaction overheads on region server.2. Prevent large spikes in read latency.

### SOLUTION

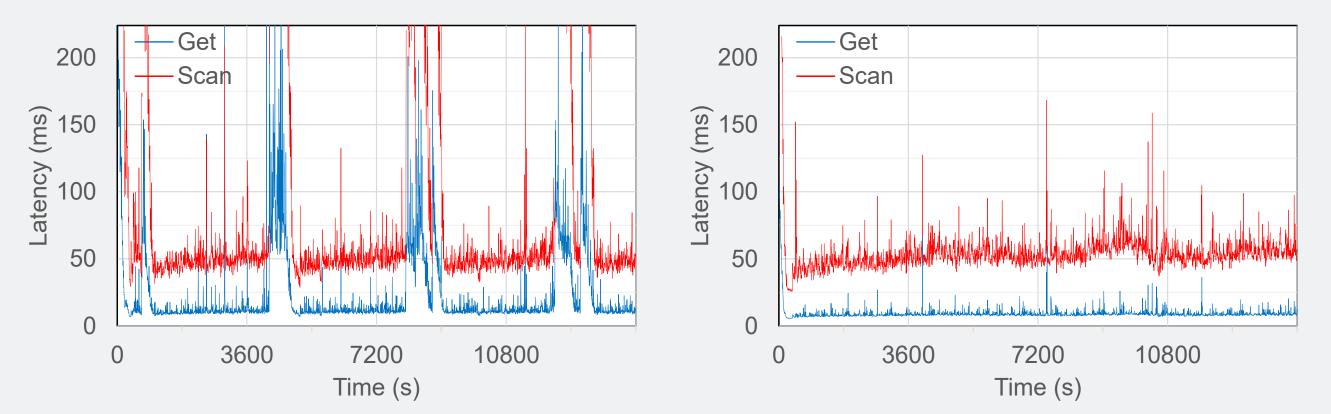
- **E** Compaction Offloading
  - Offload compactions to specialized *compaction servers*.
    Dedicate region server resources to workload execution.

1x compaction server (CS).

0 300 600 900 Time (s) Fig. 1 – Standard Compaction



**SCALABILITY** 

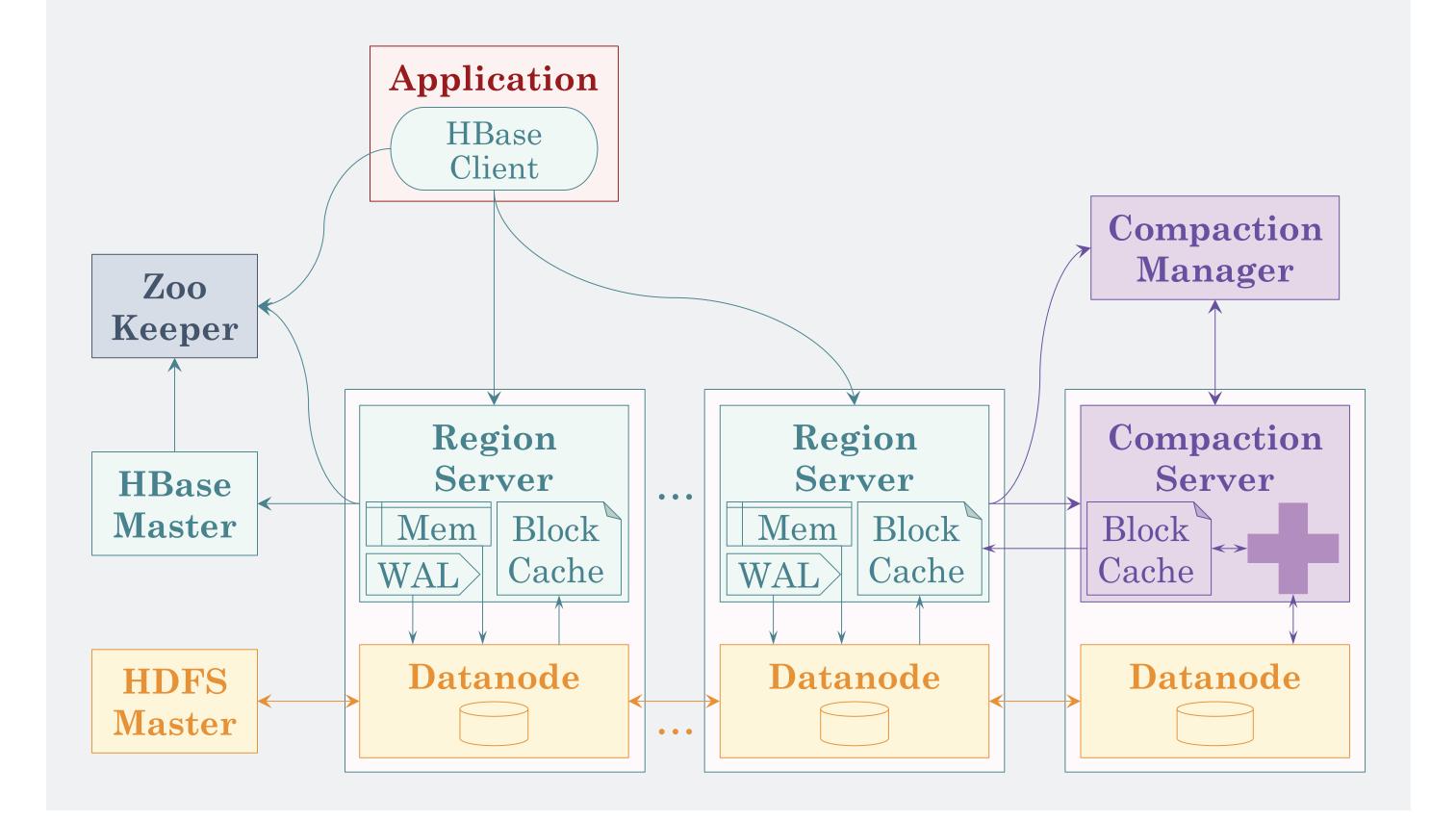


#### **E Remote Caching**

- Compaction server caches compaction results locally.
- Region server reads back results over network.

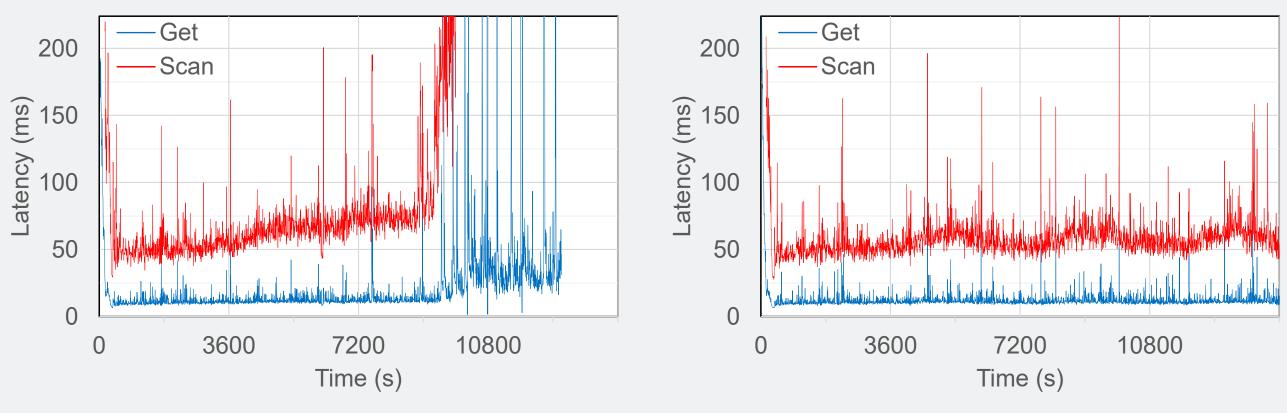
#### **E Incremental Warmup**

- Do not evict invalidated file blocks en masse.
- Gradually phase old data out, block by block.
- Replace with new data from remote cache.
- Sequential transfer (files are already sorted).





#### Fig. 5 – Offloaded 5x RS - 1x CS



#### Fig. 6 – Under-Provisioned 10x RS - 1x CS

## Fig. 7 – Balanced 10x RS - 2x CS

Compactions pile up, overloading C the single compaction server. ac

Compactions are distributed across two compaction servers.

# REFERENCES

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### RESULTS

- Compaction server assumes execution and overheads.
  - Compactions are shorter; read latency improves.
- Cache misses less costly; reads faster over network vs. disk.
- Incremental warmup eliminates cache misses altogether.
- Multiple compaction servers allow for load balancing.

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