LSM-trie: An LSM-tree-based Ultra-Large Key-Value Store for Small Data

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The Challenge on Today's Key-Value Store

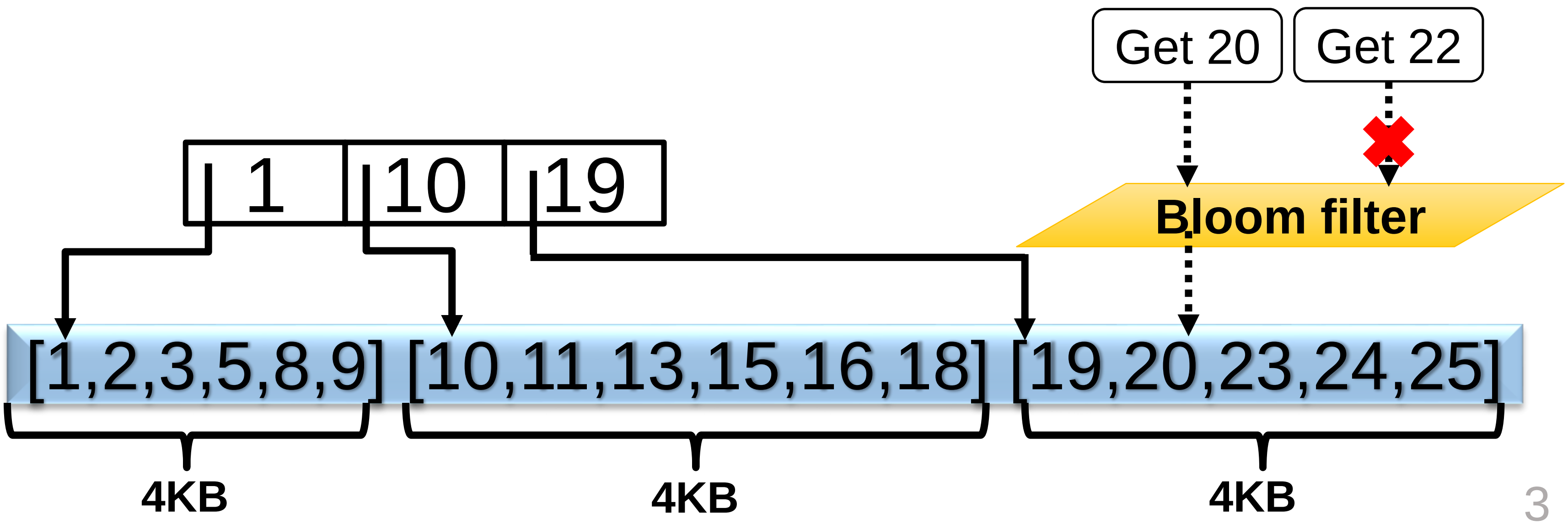
- Trends on workloads
  - Larger single-store capacity
    - **Multi-TB SSD**
    - **Flash array of over 100 TB**
  - Smaller key-value items
    - **In a Facebook KV pool 99% of the items are ≤ 68B.**
- **Large metadata set on a single node**

Consequences of a Large Metadata Set

- Less caching space for hot KV items.
  - Low hit ratio compromises system throughput.
- Long warm-up time.
  - It may take tens of minutes to read all metadata into memory.
- High read cost for out-of-core metadata.
  - It's expensive to read multiple pages to serve a single GET.
- LevelDB has managed to reduce the metadata size.

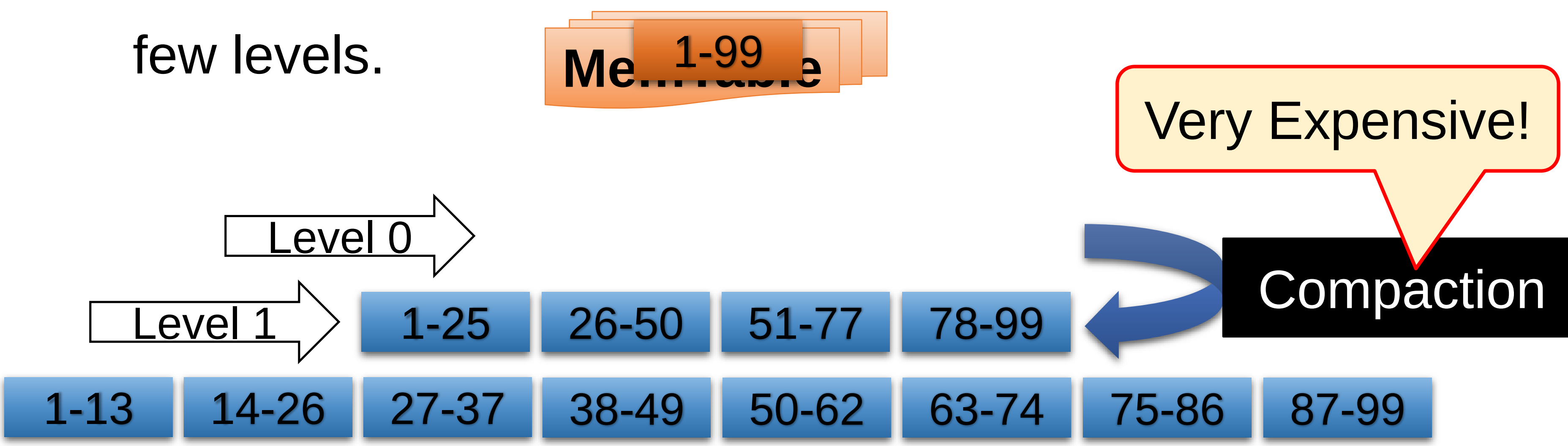
LevelDB Reduces Metadata Size with SSTable

- To construct an **SSTable**:
  - – Sort data into a list.
  - – Build memory-efficient **block-index**.
  - – Generate **Bloom filters** to avoid unnecessary reads.
- How to support insertions on SSTable?



Reorganizing Data Across Levels

- LSM-tree (Log-Structured Merge-tree)
  - New items are first accumulated in **MemTable**.
  - Each filled MemTable is converted to an SSTable at **Level 0**.
  - LevelDB conducts **compaction** to merge the SSTables.
- A store can **exponentially grow** to several TBs with a few levels.



A Closer Look at Compaction

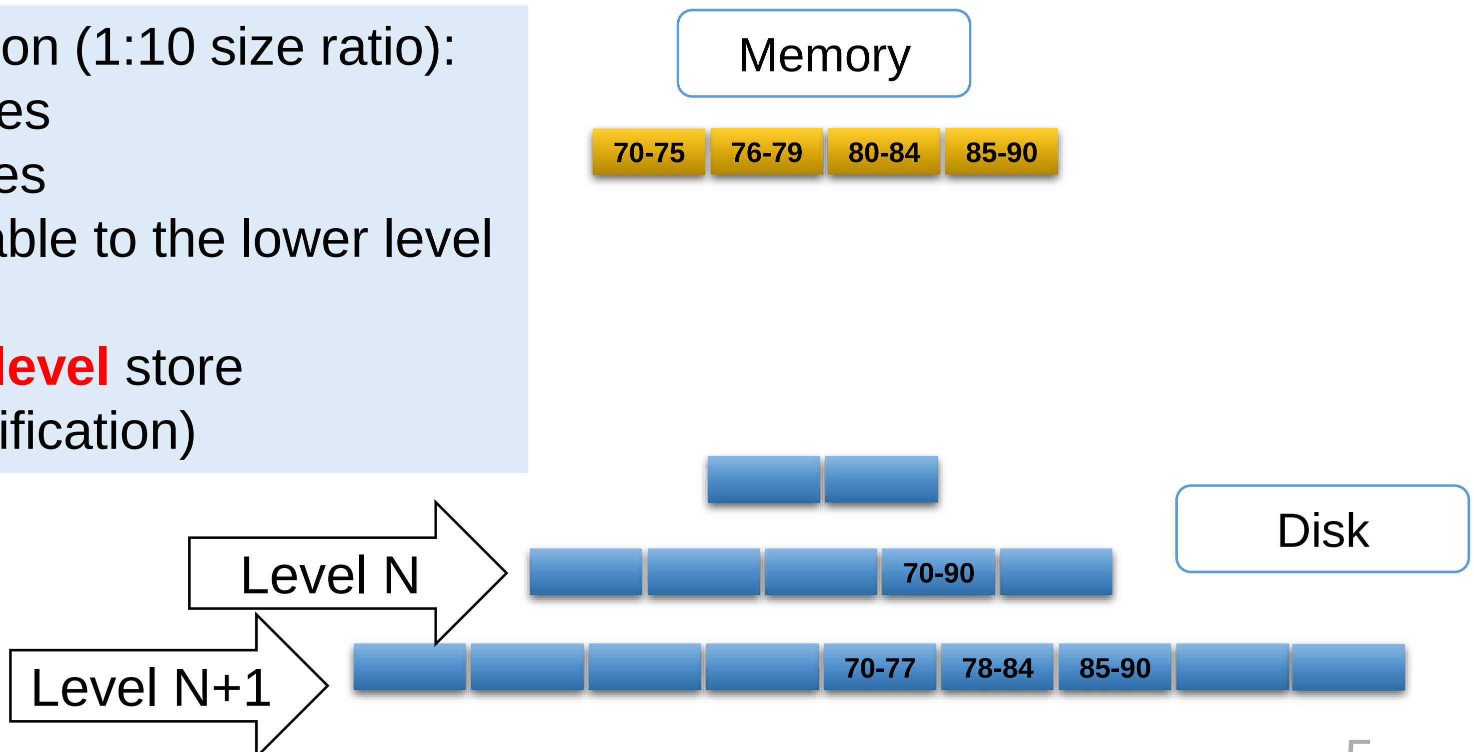
Steps in compaction:

1. Read overlapping SSTables into memory.
2. Merge-Sort the data in memory to form a list of new SSTables.
3. Write the new SSTables onto the disk to replace the old ones.

In one compaction (1:10 size ratio):

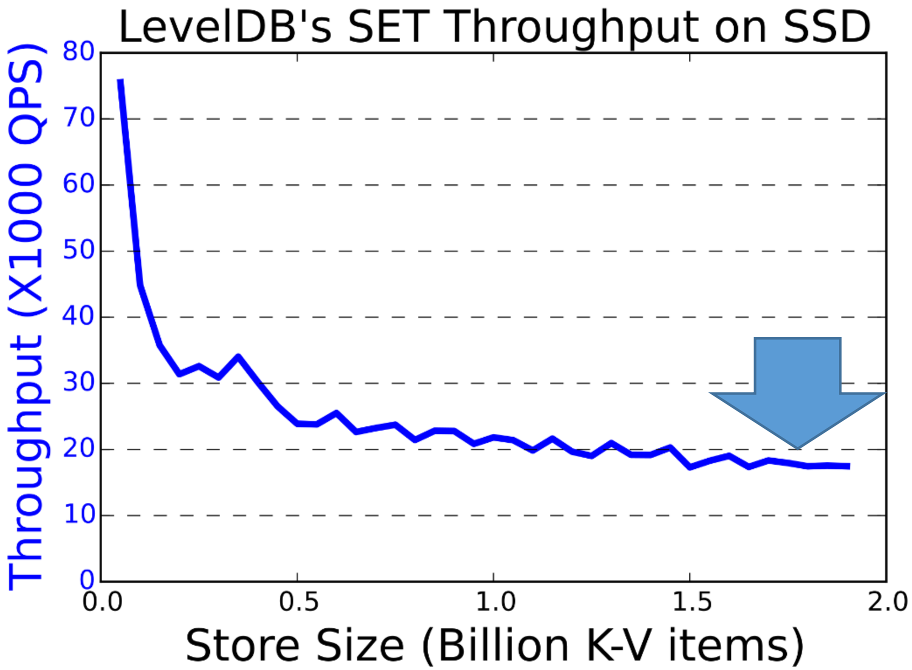
- Read 11 tables
- Write 11 tables
- Add only **1** table to the lower level

45x WA for a **5-level** store
(WA: write amplification)



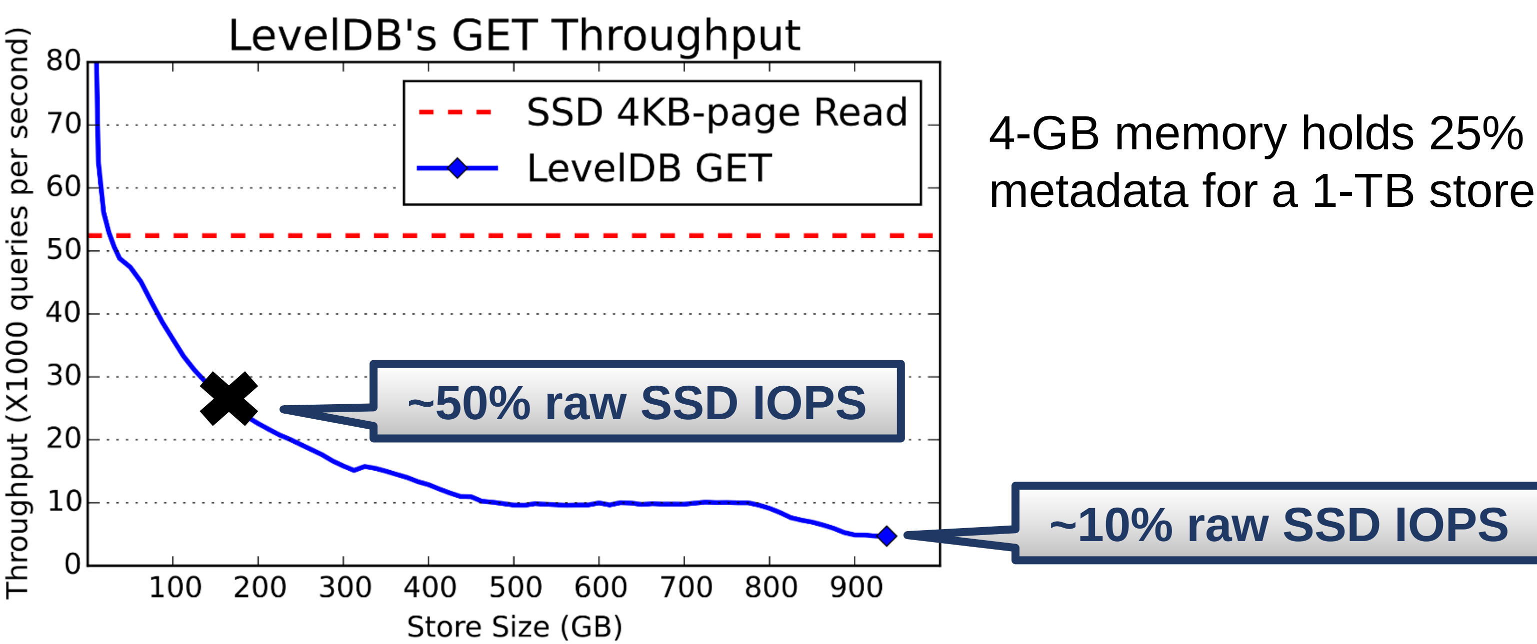
Compaction can be very Expensive

- The workload:
  - PUT 2 billion items of random keys (~250GB).
  - 16-byte key and 100-byte value.
- PUT throughput reduces to **18K QPS (2MB/s).**



Metadata I/O is Inefficient

- Facts about LevelDB's metadata:
  - Block Index: ~**12 bytes per block**.
  - Bloom filter: ~**10 bits per key**.
- How large is it in a 10-TB store of 100-byte KV items?
  – **155GB metadata:** 30 GB block index + 125 GB Bloom filter.



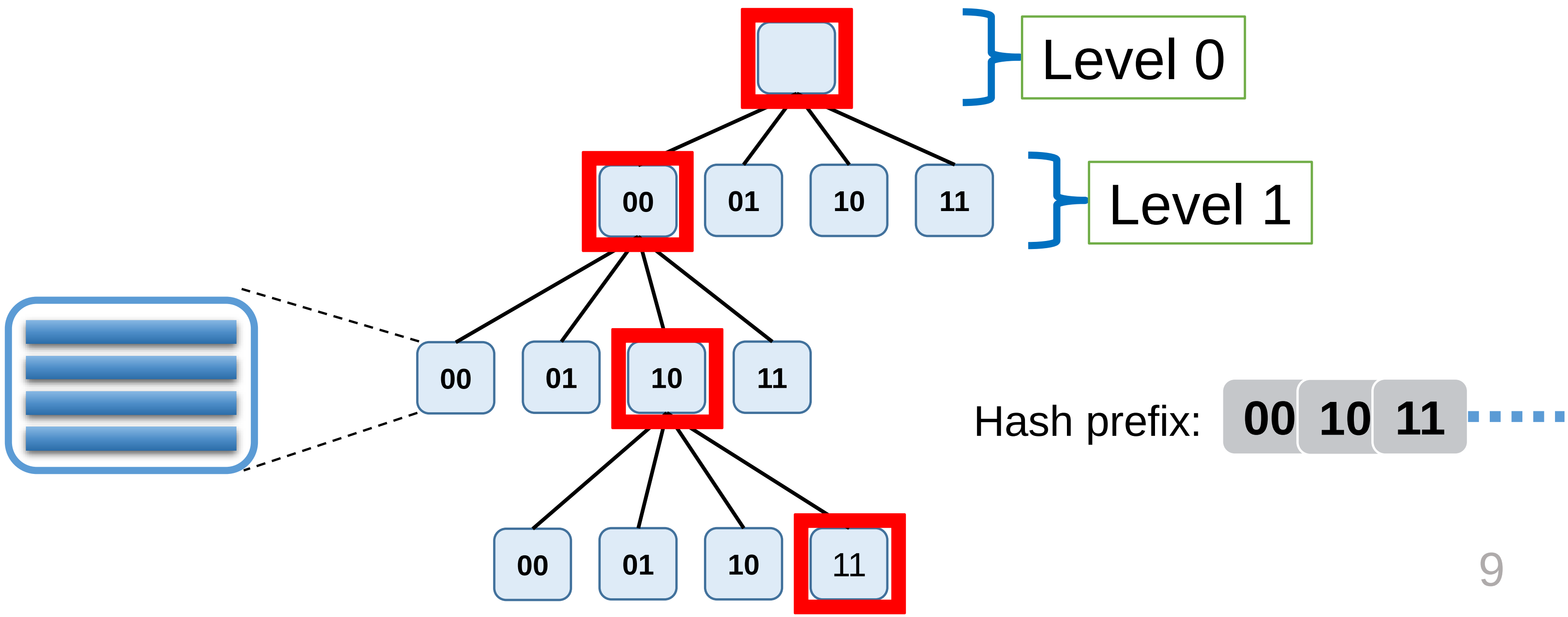
4-GB memory holds 25% of the metadata for a 1-TB store.

Our solution: LSM-trie

- Build an ultra-large KV store for small data.
  - Using a trie structure to improve **compaction efficiency**.
  - **Clustering Bloom filters** for efficiently reading out-of-core metadata.

Organizing Tables in a Trie (Prefix Tree)

- KV items are located in the trie according to their hashed key.
- Each **trie node** contains a pile of immutable tables.
- The nodes at the same depth form a conceptual **level**.
- How does LSM-trie help with efficient compaction?



Efficient Compaction in LSM-trie

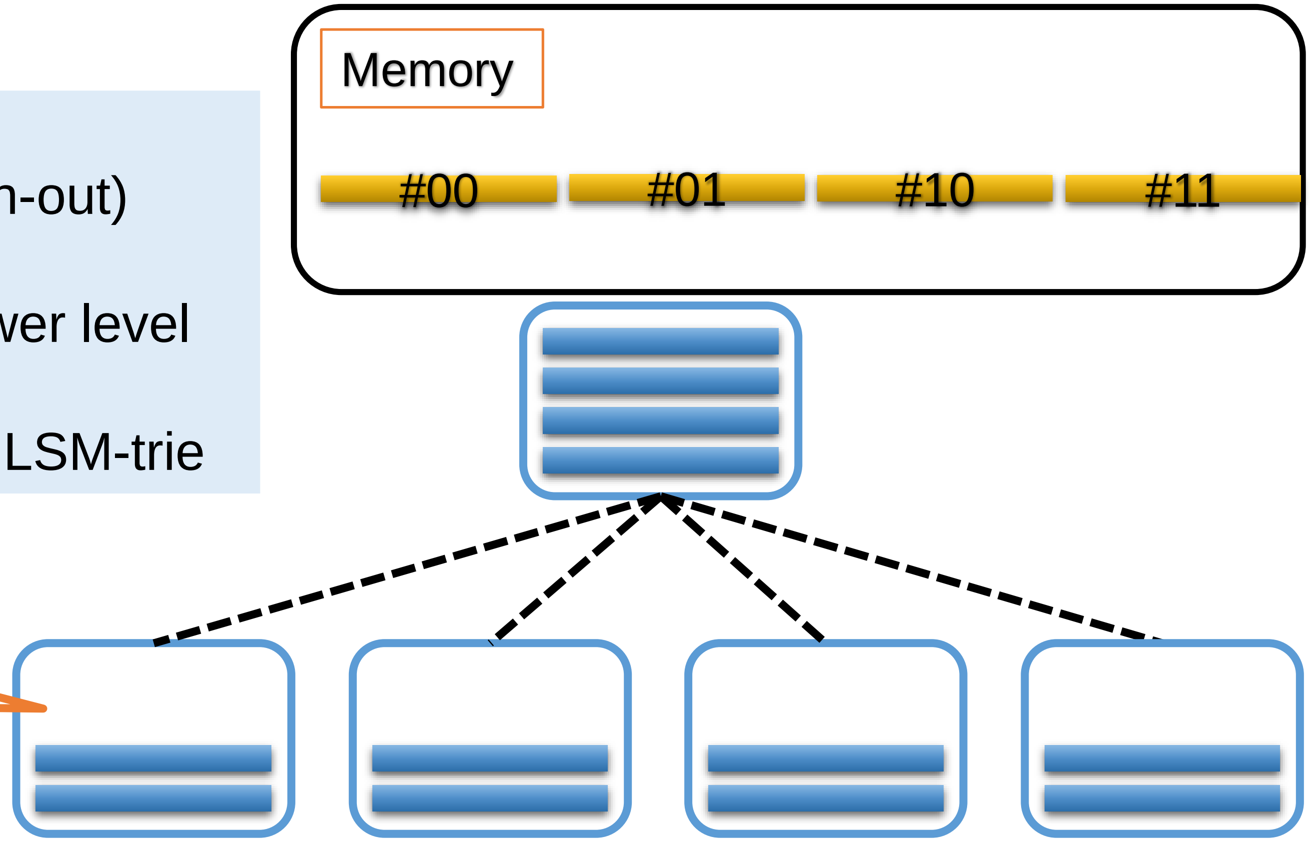
Compaction steps:

1. Read tables from **the parent node** into memory.
2. Assign the items to new tables according to hash-prefixes.
3. Write new tables into its **child nodes**.

For one compaction:

- Read 8 tables (1:8 fan-out)
- Write 8 tables
- Add 8 tables to the lower level

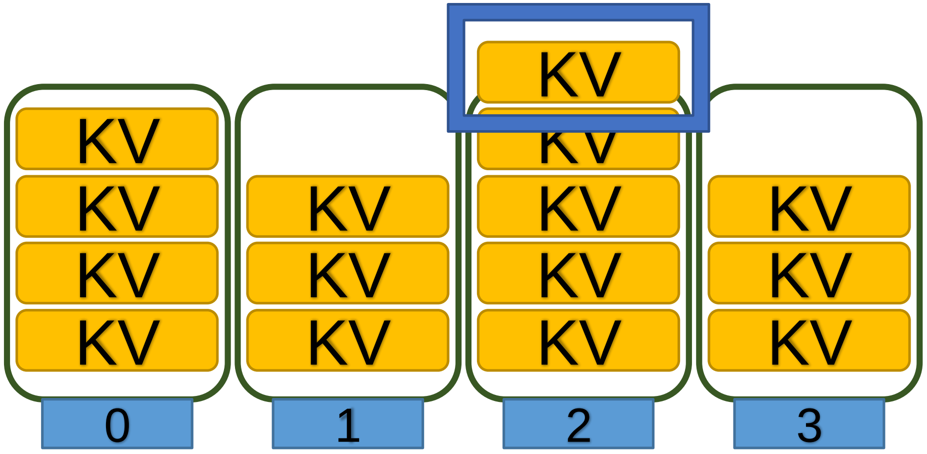
Only **5x** WA for a **5-level** LSM-trie



Tables linearly grow at each node

Introducing HTable*

- **HTable**: Immutable hash-table of key-value items
  - Each **bucket** has 4KB space by default.
- Some buckets have overflowed items.
  - Migrating the overflowed items.

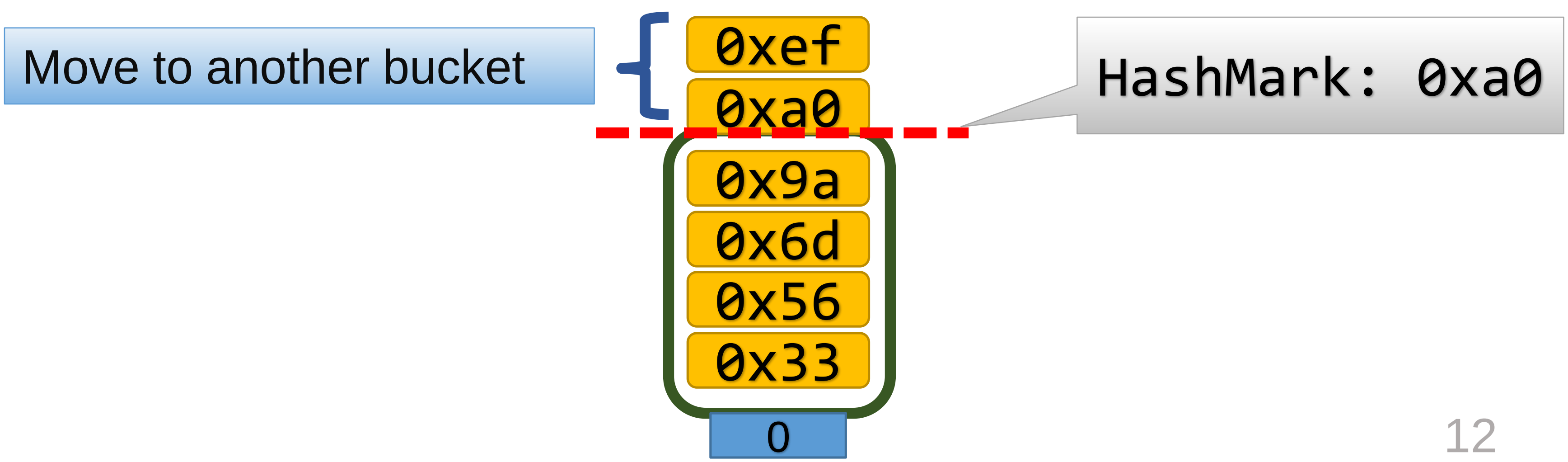


Bucket ID: 0 to 3

*It's not the HTable in HBase.

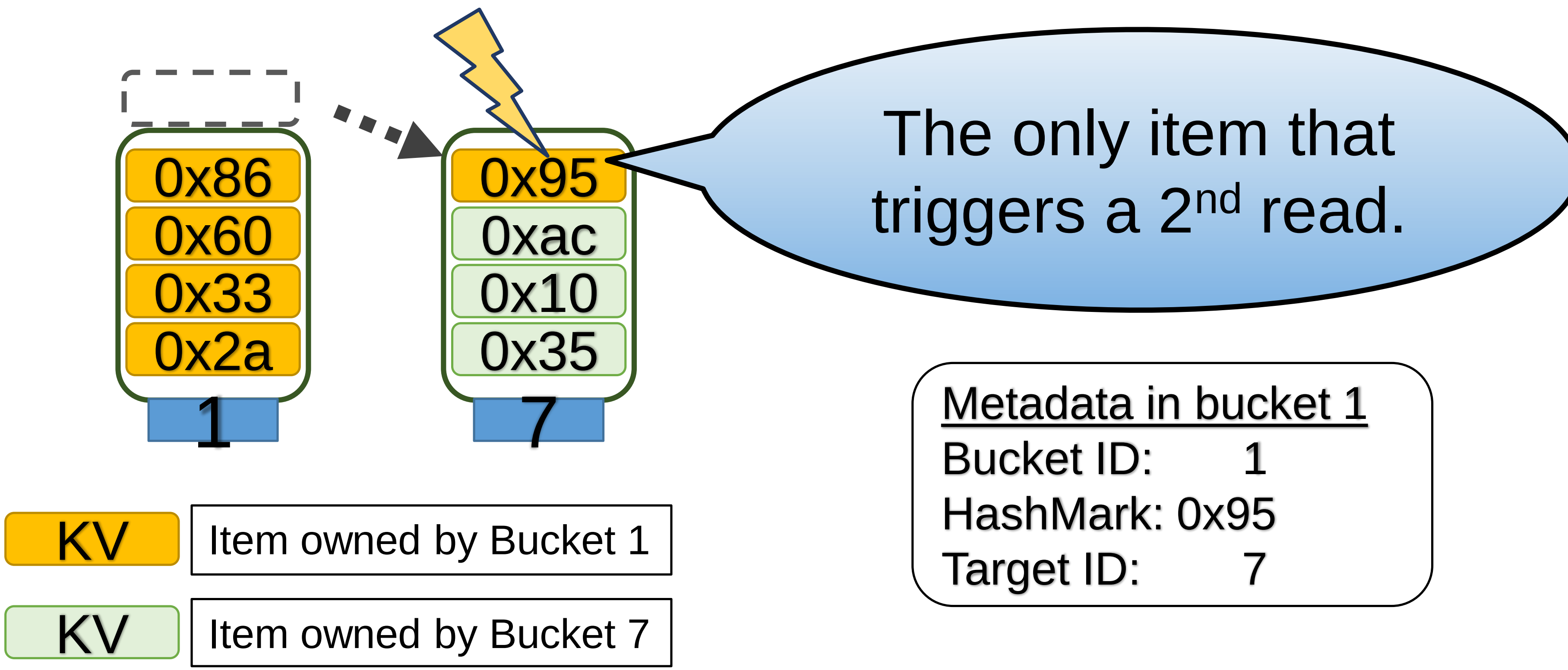
Selecting Items for Migration

- Sorting items in a bucket according to their key's hash.
- Migrating the items above the **watermark** (**HashMark**).
- Recording the HashMark and the corresponding IDs.
  - **2B Source ID, 2B Target ID, 4B HashMark**



Caching HashMarks for Efficient GETs

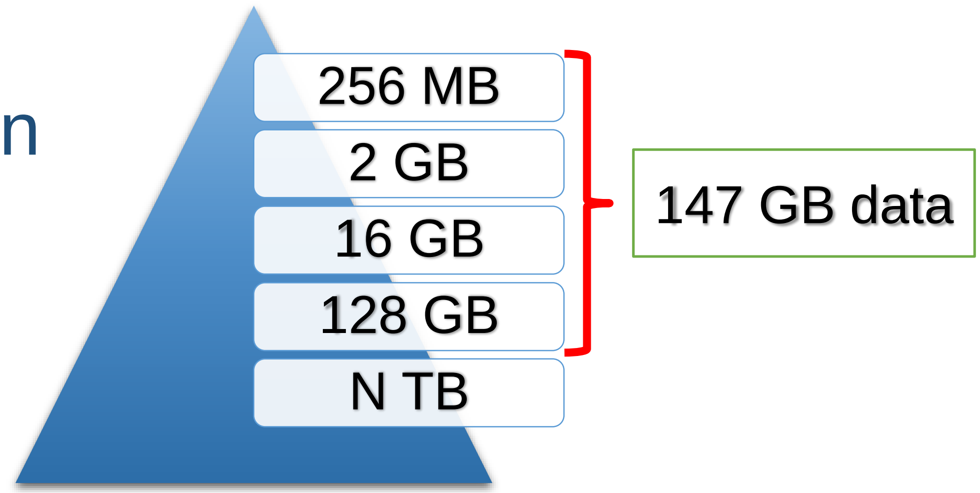
- Only cache HashMark for most overloaded buckets.
  - **1.01 amortized reads** per GET.
  - **A 1-TB store only needs ~400MB in-memory HashMark.**



Most Metadata is in the Last Level

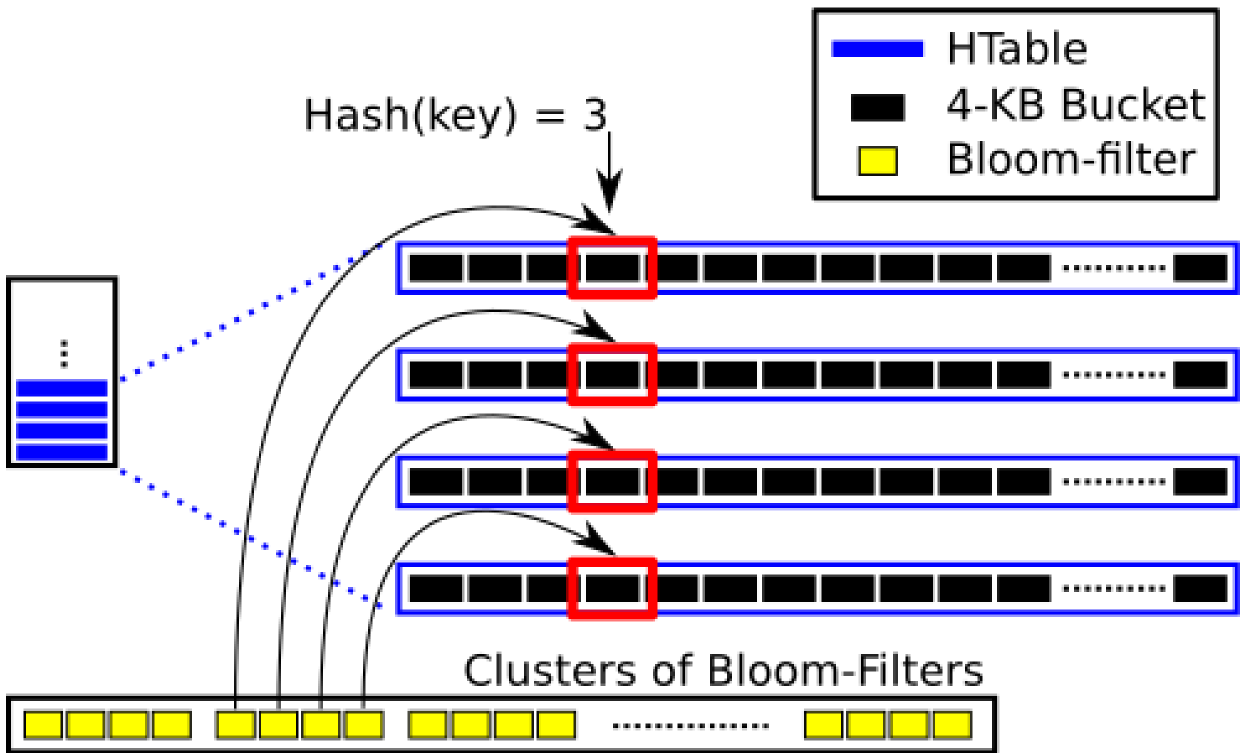
- **The first four levels** contain 1.9 GB Bloom filters (BF).
- **The last level** may contain over one hundred GB BFs.
- We **explicitly cache** the BFs for **Level 0 to Level 3.**
- The BFs at **the last level are managed differently**.

Data size distribution across the levels:



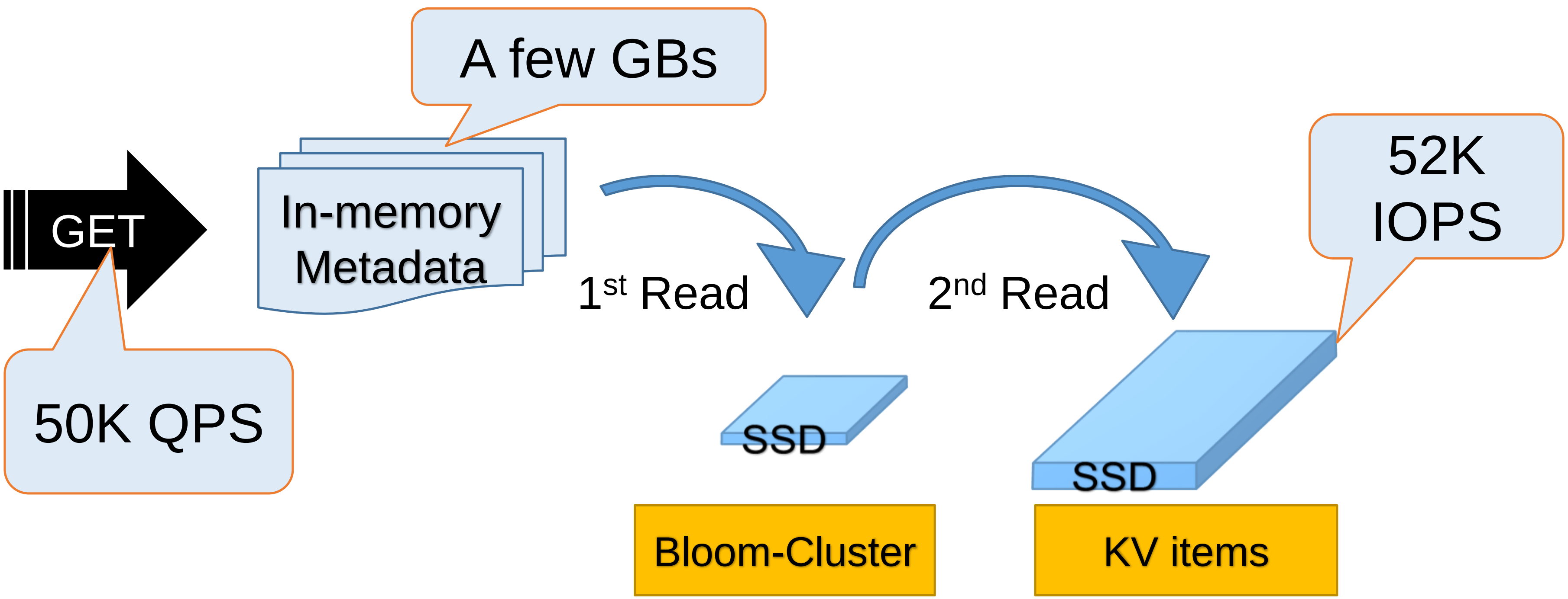
Clustering Bloom Filter for Efficient Read

- Each hash(key) indicates a **column** of 4-KB buckets.
- We collect all the BFs in a column to form a **BloomCluster**.
- Each GET requires **one SSD read** for all the out-of-core BFs.

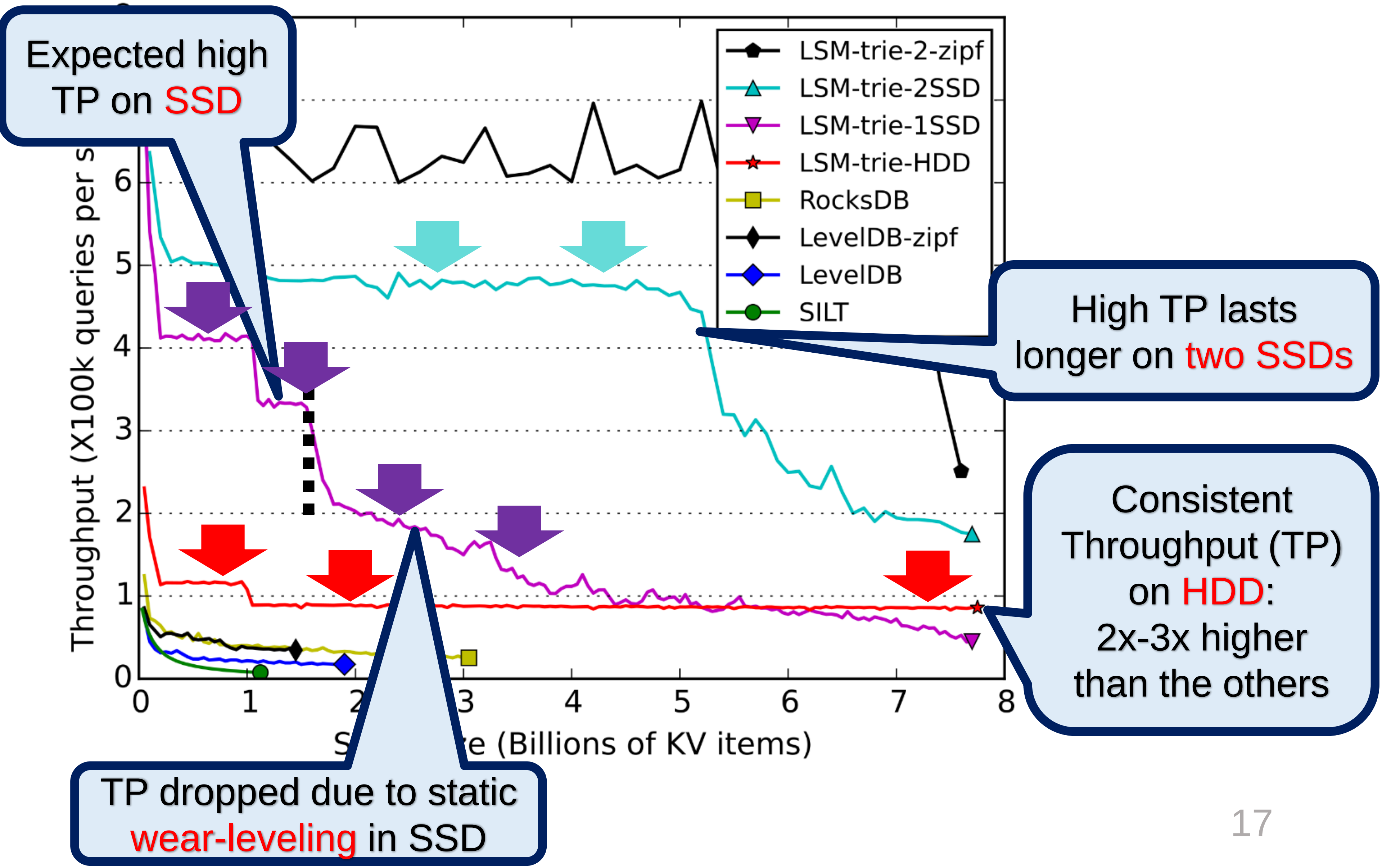


Exploiting Full SSD Performance

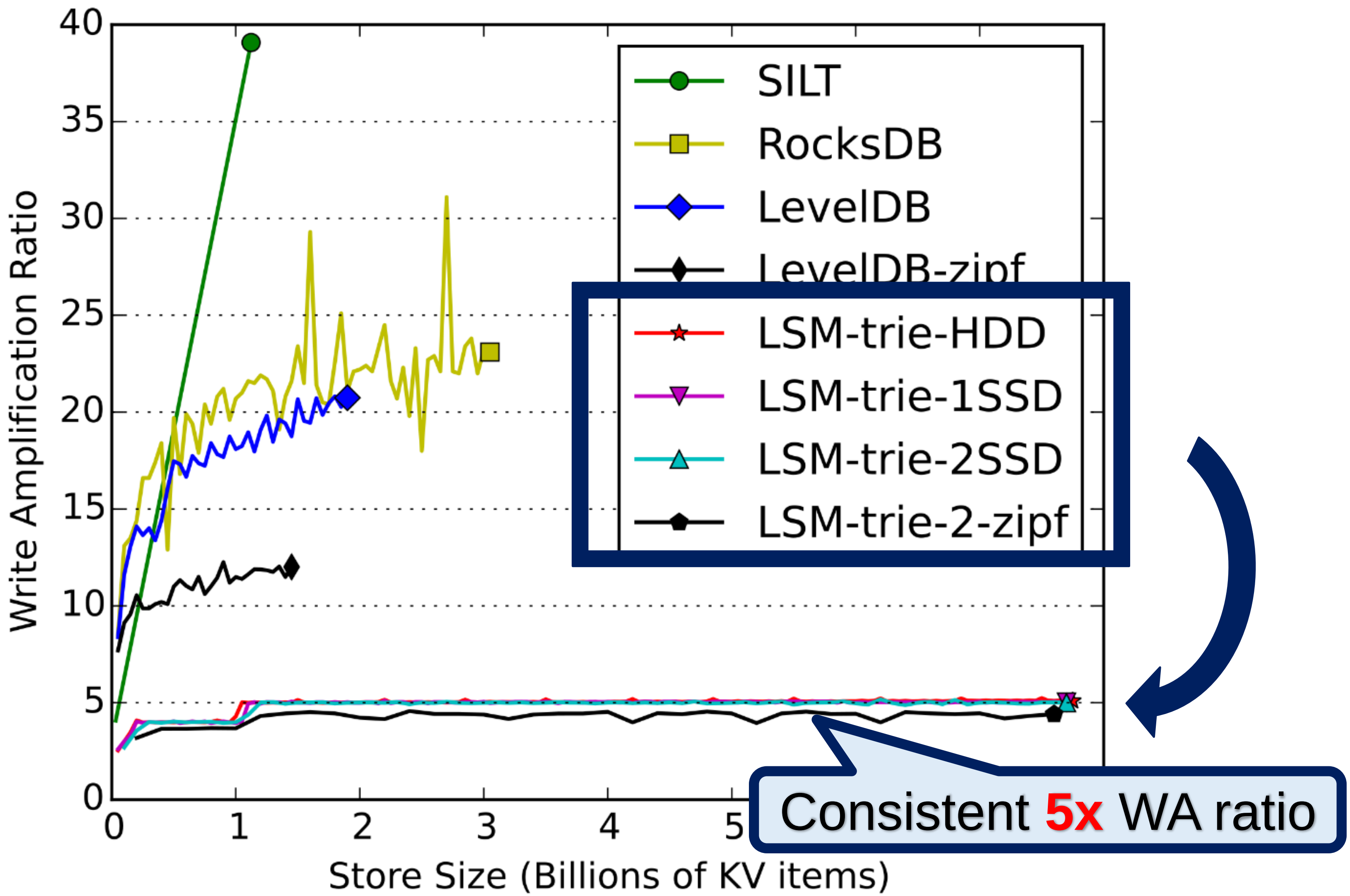
- Using an additional small SSD to host BloomClusters.
  - e.g., a **10-TB** SSD for data + a **128-GB** SSD for metadata.
- Plenty of memory space is left for your **data cache**!



Performance Evaluation of PUT

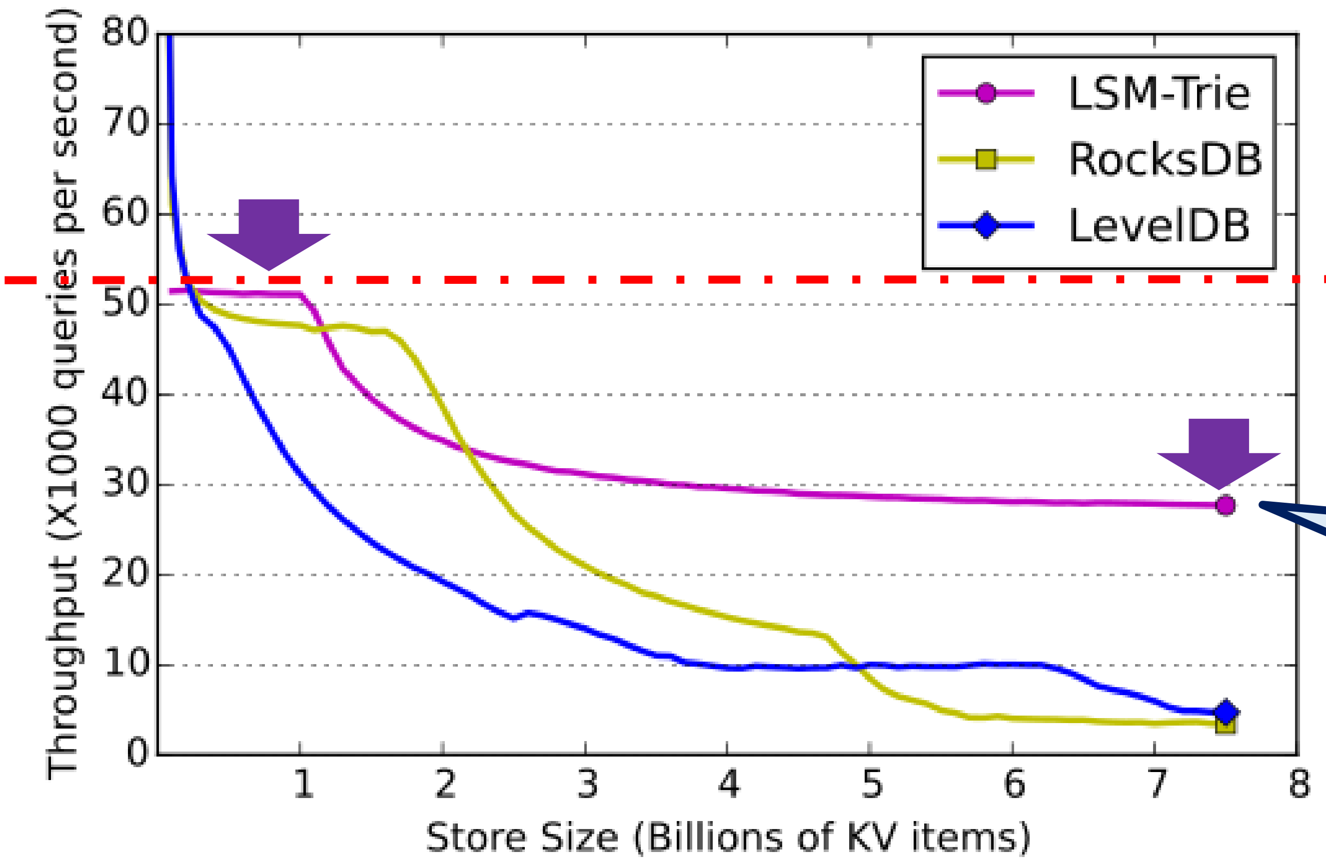


Write Amplification Comparison



Read Performance with 4GB Memory

Only one SSD is used.



SSD IOPS

~50% raw SSD IOPS

*No data cache for LSM-trie

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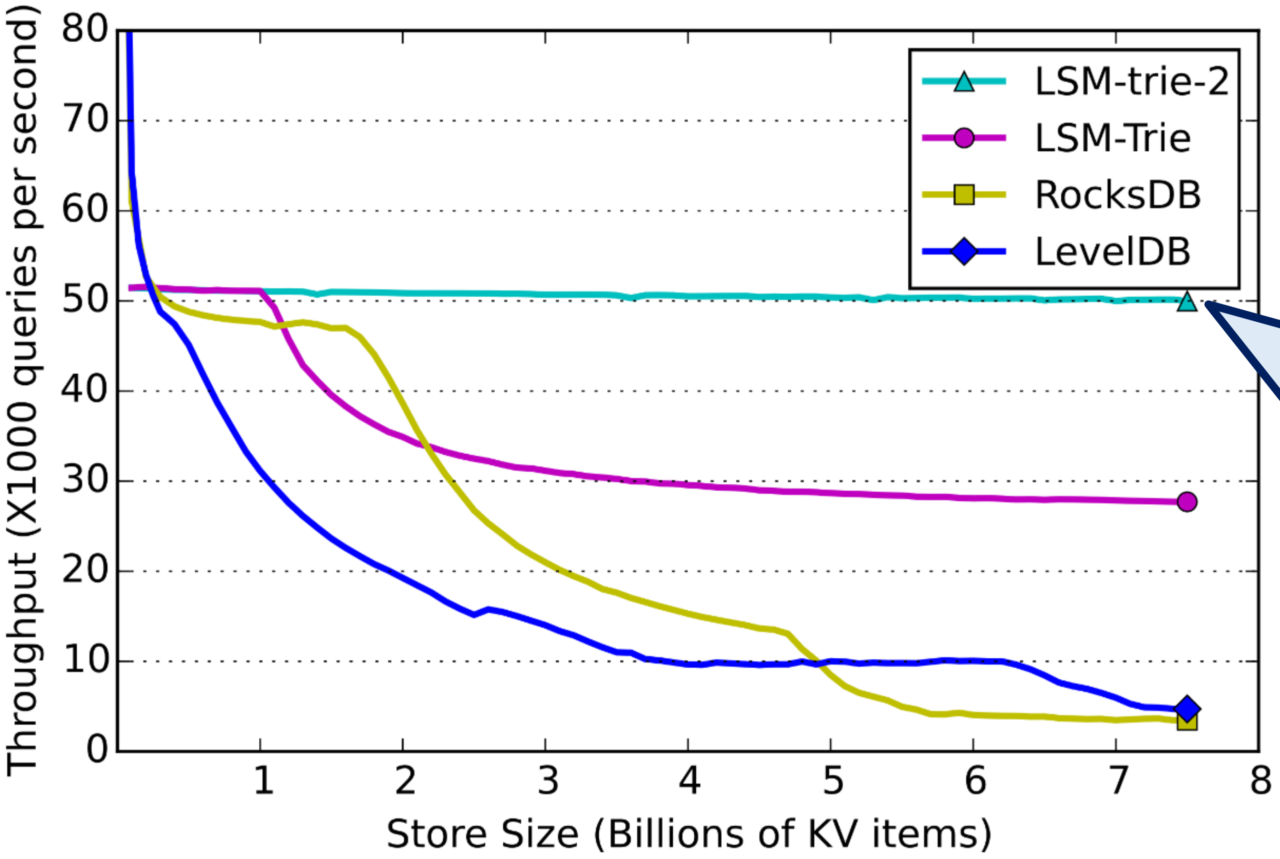

Gains 96% raw SSD IOPS with an additional SSD.

*No data cache for LSM-trie

Summary

- LSM-trie is designed to manage a large set of small data.
- It reduces the write-amplification by an order of magnitude.
- It delivers high throughput even with out-of-core metadata.

The LSM-trie source code can be downloaded at:

https://github.com/wuxb45/lsm-trie-release

Thank you!

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Q & A