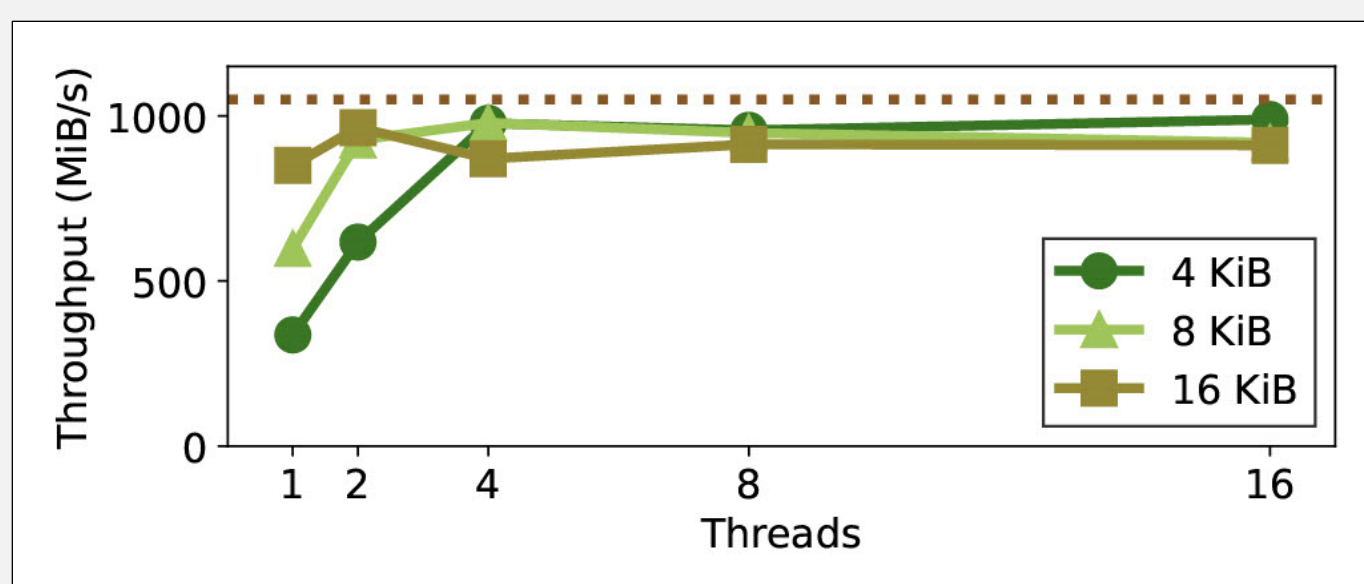


TreeLine: An Update-In-Place Key-Value Store for Modern Storage

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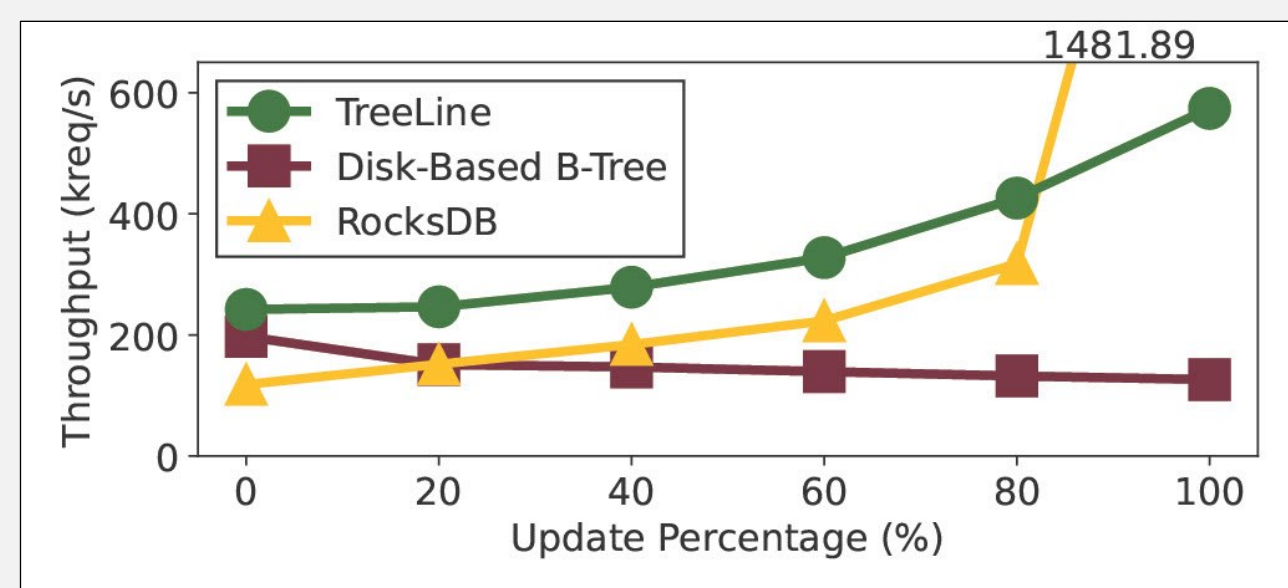
Motivation



- Modern persistent key-value stores, such as RocksDB [1] and LevelDB [2], typically use log-structured merge trees (LSMs) [3].
- Stellar write performance: large sequential writes exploit the high sequential throughput.
- Slow read performance: need caches, Bloom filters [4,5], compaction strategies [6,7,8]—complex and hard-to-tune. [9]

Random Writes \approx Sequential Writes on NVMe SSDs

- Random write throughput across (i) request sizes, and (ii) number of writing threads.
- With high parallelism, can reach advertised peak sequential write throughput [10].



Both experiments on an Intel DC P4510 NVMe SSD.

LSMs Leave Read Performance on the Table

- Zipfian-distributed ($\theta = 0.79$) workload of reads, updates, and scans on 64 B records.
- Of the requests that are not updates, 10% are range scans and the rest are point reads.
- For read-heavy, the disk-based B-tree outperforms/is competitive against RocksDB.
- TreeLine can outperform both systems all the way up to 80% updates.

Design Overview

Key Idea A: Record Caching

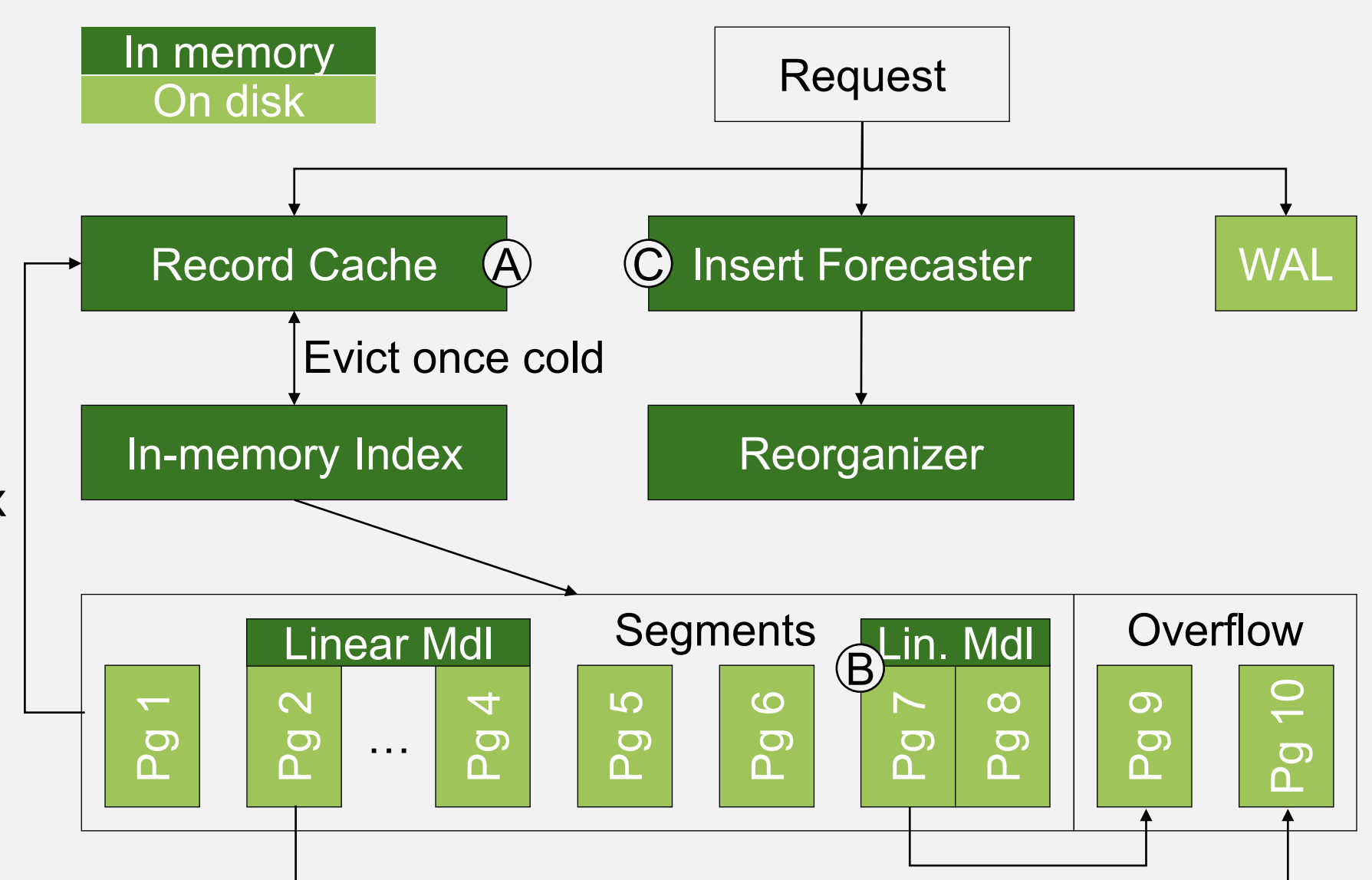
- Key-to-page mapping is expensive to change in update-in-place design.
- But variable hotness among records on the same page.
- **Solution:** Only cache records, to increase memory efficiency.

Key Idea B: Page Grouping

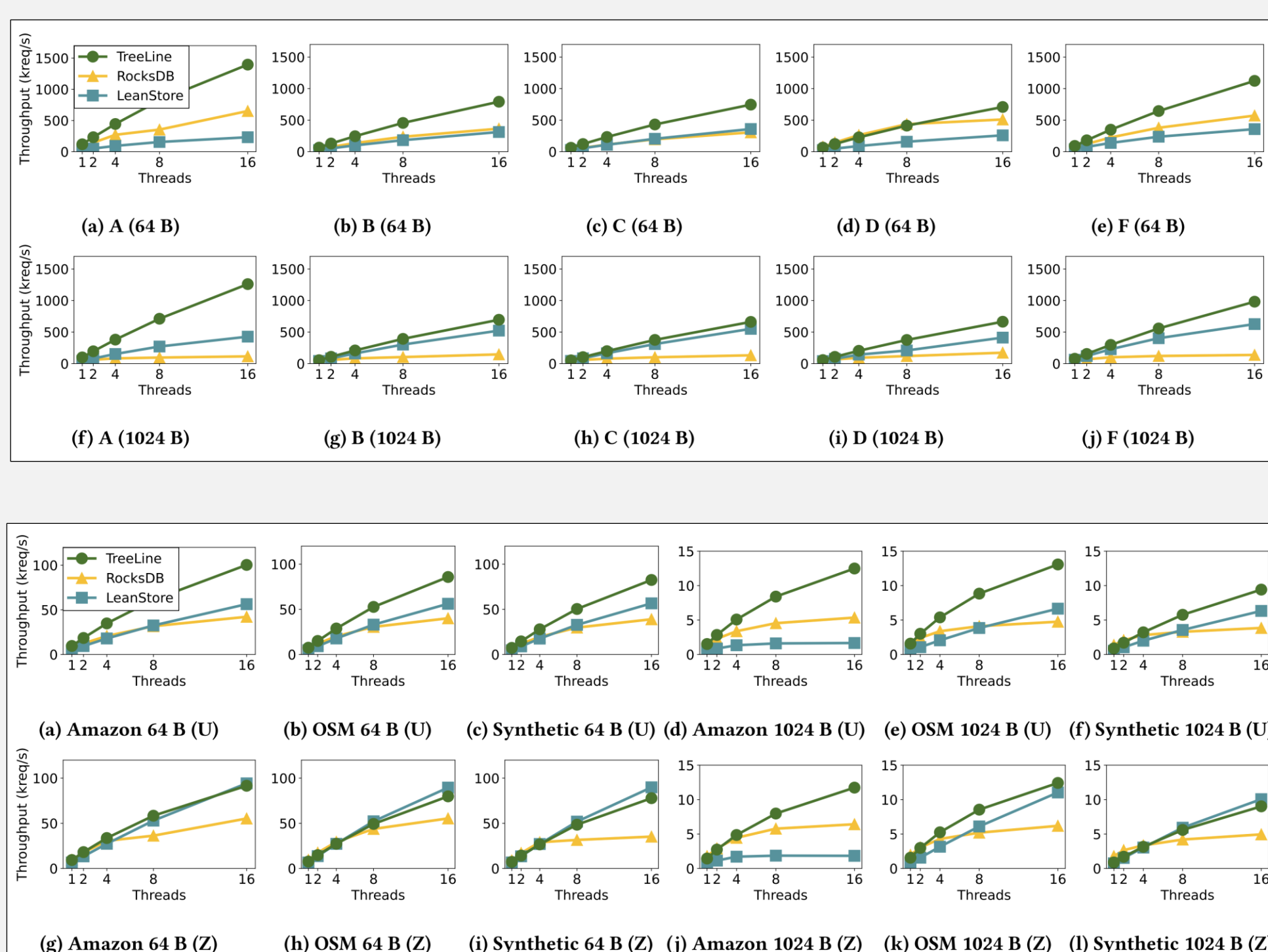
- Unlike writes, sequential reads still faster vs. random reads on modern SSDs.
- Pages must be sequential to make scans fast.
- **Solution:** Group pages into contiguous segments. Use linear models to index records within segments.

Key Idea C: Insert Forecasting

- To avoid constant reorganization, pages should have some empty space.
- But too much empty space increases I/O amplification.
- **Solution:** Leave empty space based on epoch-based insert forecast.



Evaluation

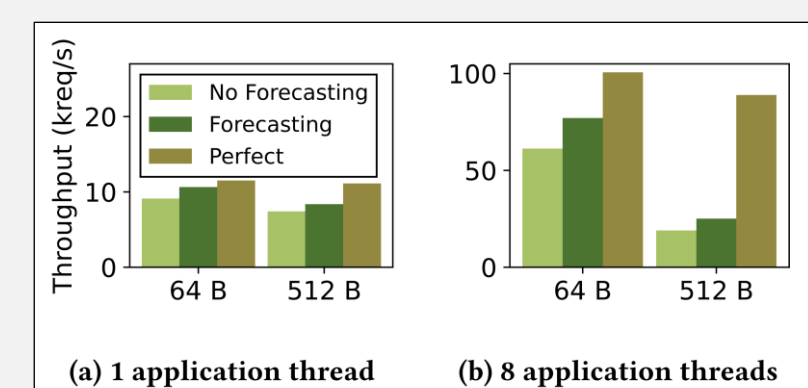


Point Workloads

- TreeLine outperforms RocksDB (LeanStore) by **1.62x (2.81x)** and **2.99x (1.53x)** on average for **64 B/1024 B** records.

Scans

- With 16 request threads, for uniform scans, TreeLine outperforms RocksDB (LeanStore) by **2.21x (1.58x)** and **2.50x (2.80x)** on average for **64 B/1024 B** records.
- With 16 request threads, for Zipfian-distributed scans, TreeLine outperforms RocksDB (LeanStore) by **1.74x (0.91x)** and **1.88x (1.86x)** on average for **64 B/1024 B** records.



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