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

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Code: github.com/mitdbg/treeline
Paper: tinyurl.com/treeline-paper

Photo by Richard Main on Unsplash

What this talk is about

The Opportunity and Problem

- Disk-based key-value stores: usually log-structured merge trees (LSMs)
  - High write performance (sequential), competitive on reads
- NVMe SSDs: Parallel random writes ≈ sequential write performance
- Are LSMs still the right choice?

This Work: TreeLine – Making update-in-place great again

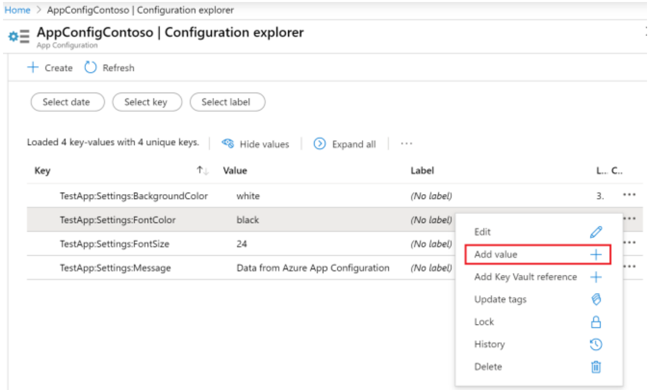
- Update-in-place design to provide stellar read performance
- **Our angle:** Leverage workload patterns to be competitive at writes
- **Key results:** Up to **10.95x** and **7.52x** over RocksDB, LeanStore on YCSB

The Motivation

Key-value stores? Skew?

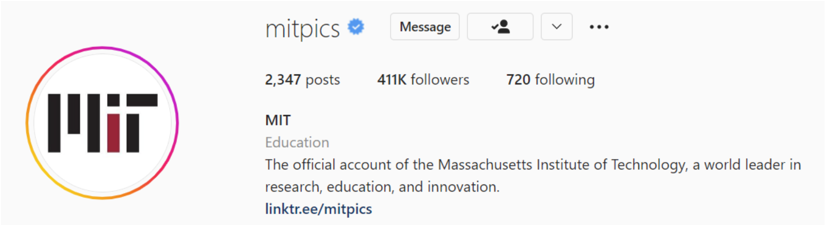
Persistent, concurrent KVSs abound

Configurations



User preferences

Profile metadata



Not all keys are created equal

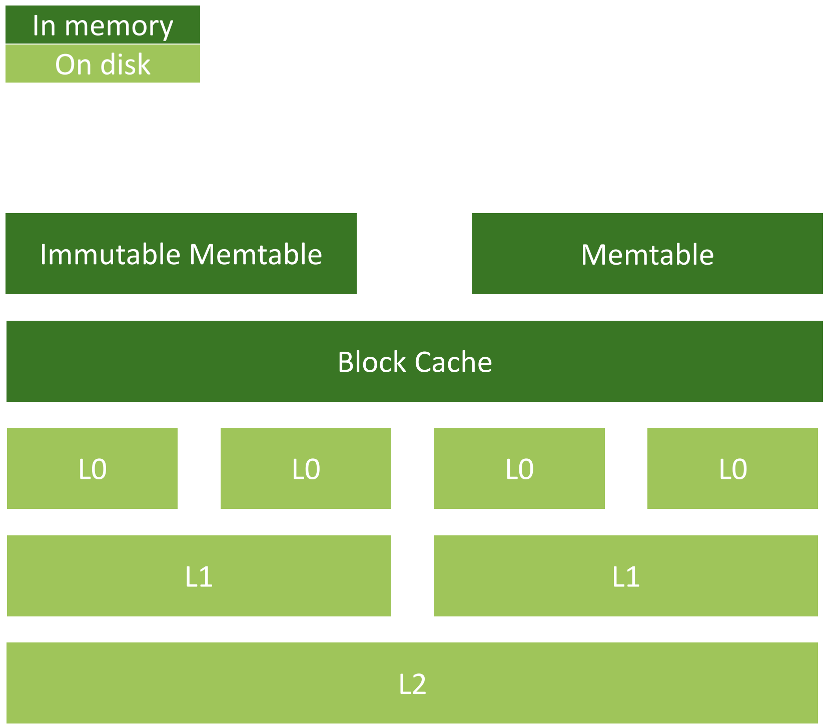
- Updates >> Inserts
- Varying hotness
- Hotness independent of key
- Frequently-updated and frequently-read keys not necessarily the same.
- How to handle such a workload efficiently?

The Orientation

From log-structured databases to storage interfaces

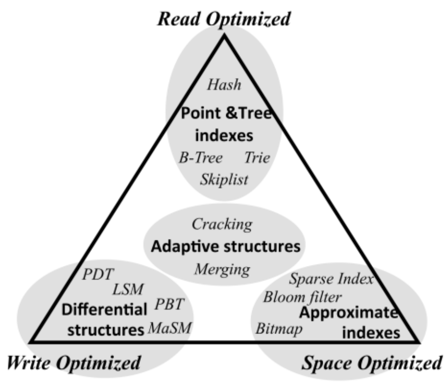
LSM-trees efficiently absorb writes

- Usual solution: Log-Structured Merge (LSM) tree.
- Basic principles:
  - Buffer writes.
  - Write to disk when full.
  - Periodically “compact” logarithmically.
  - Read from memtables, or from cache; fresher versions are in lower-numbered levels.



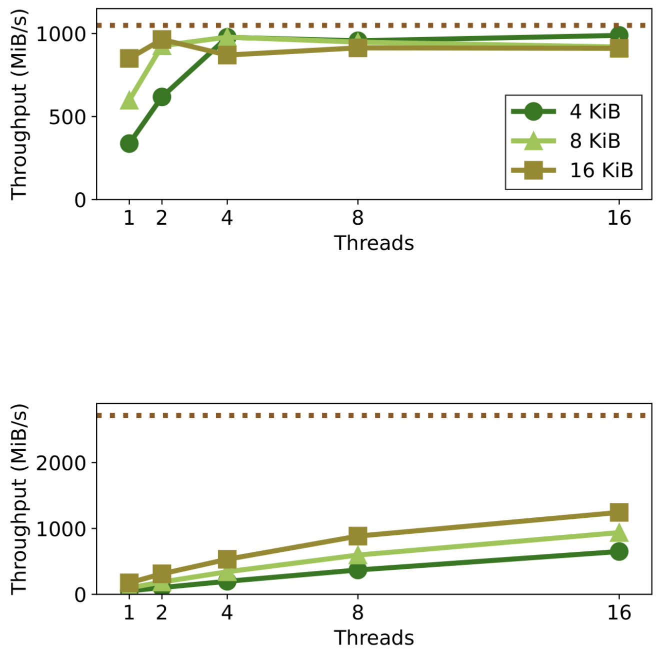
Some RUM-induced thoughts

- RUM conjecture [Athanassoulis et al. 2016] – access methods trade off:
  - **R**ead performance
  - **U**pdate performance
  - **M**emory performance
- Efficient **updates**: dump into memtable and flush periodically.
- LSM trees: slow **reads** unless hot write keys match hot read keys.
- High **memory** use: same key can be in many places.



Modern storage provides new trade-offs

- HDDs: sequential access unlocks performance.
- Flushing memtable achieves high throughput.
- NVMe SSDs: random writes are also performant
- Sequential *reads* still better than random.
  - Speculative pre-fetching.
  - Closer for large blocks.
- Can we improve read and memory performance?

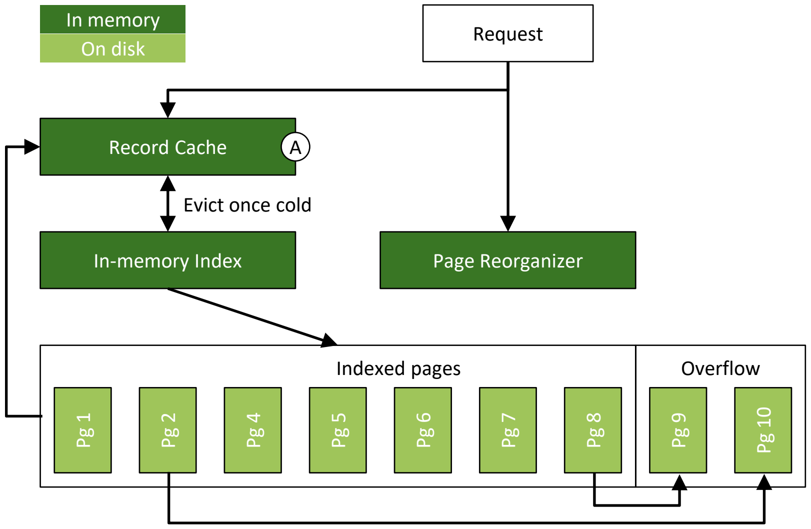


The Innovation

How to make an update-in-place design workable

Workload skew doesn’t care about layout

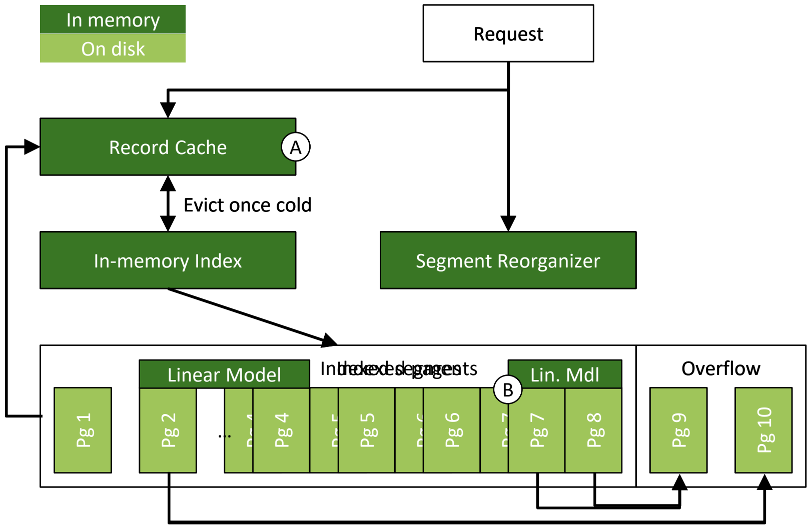
- LSMs use *block* (page) cache.
- One hot record in each page?
- **Key Idea A**: use instead a *record* cache.
  - Lower memory amplification.
  - Higher I/O amplification.
  - Balance in our favor.
- In-memory index with one key per page.
- When page is full, allocate overflow.
- When overflow page is full, reorganize.



Key Idea B: Page Grouping

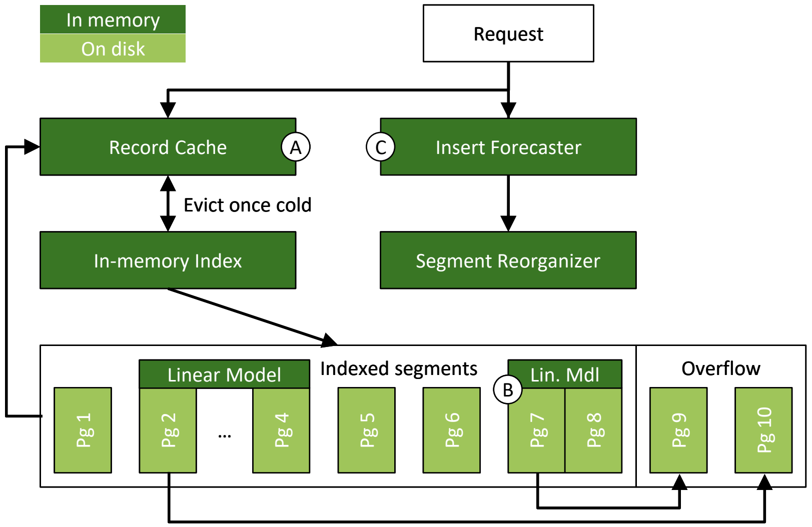
Small pages, large pages – why not both?

- Point requests? Make pages small!
- Scans? Make pages large!
- **Key Idea B**: Page grouping.
  - Co-locate pages, forming *segments.*
  - For scans, read the entire segment.
- Use linear models to shrink index.
  - Synchronization contention point.
  - Only index one key per *segment*.
  - Use model to navigate within segment.



Half-full pages are usually half-empty

- One page for a record – if full, must reorganize.
- How much space to leave?
  - Too much: Bad I/O amplification.
  - Too little: Must reorganize often.
- **Key Idea C**: Insert Forecasting.
  - Predict inserts using recent sample.
  - On reorganization, leave empty space based on estimate.



The Evaluation

So, how well does this work?

Experimental setup

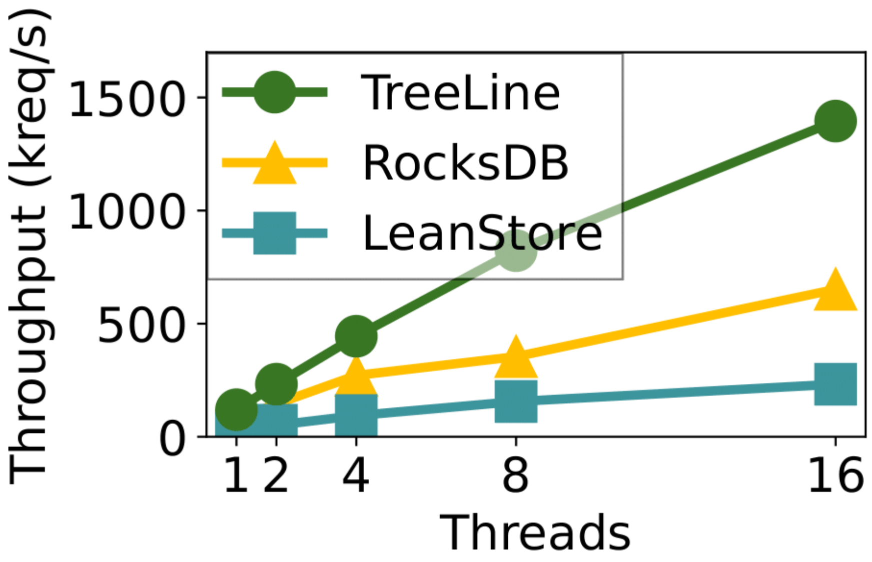
- **Hardware:**
  - 20-core 2.10 GHz Intel Xeon Gold 6230 CPU, 128 GiB of memory
  - 1 TB Intel DC P4510 NVMe SSD

- **Workload:** Yahoo! Cloud Serving Benchmark suite (YCSB)
  - Amazon reviews dataset (33 million keys), 33% fits in memory
  - Zipfian and uniform requests

- **Baselines:**
  - RocksDB (LSM)
  - LeanStore (Update-in-place)

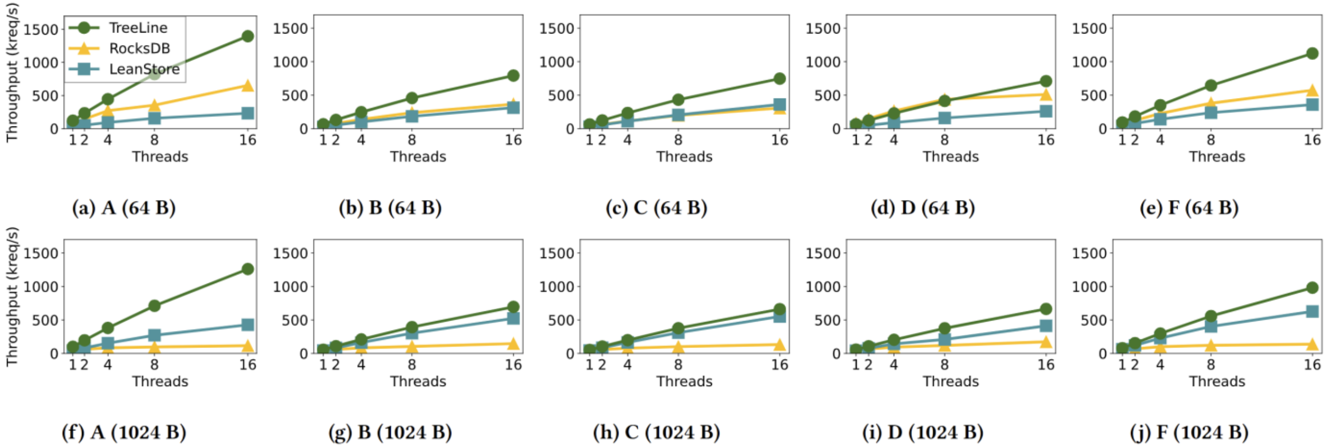
RocksDB leanstore

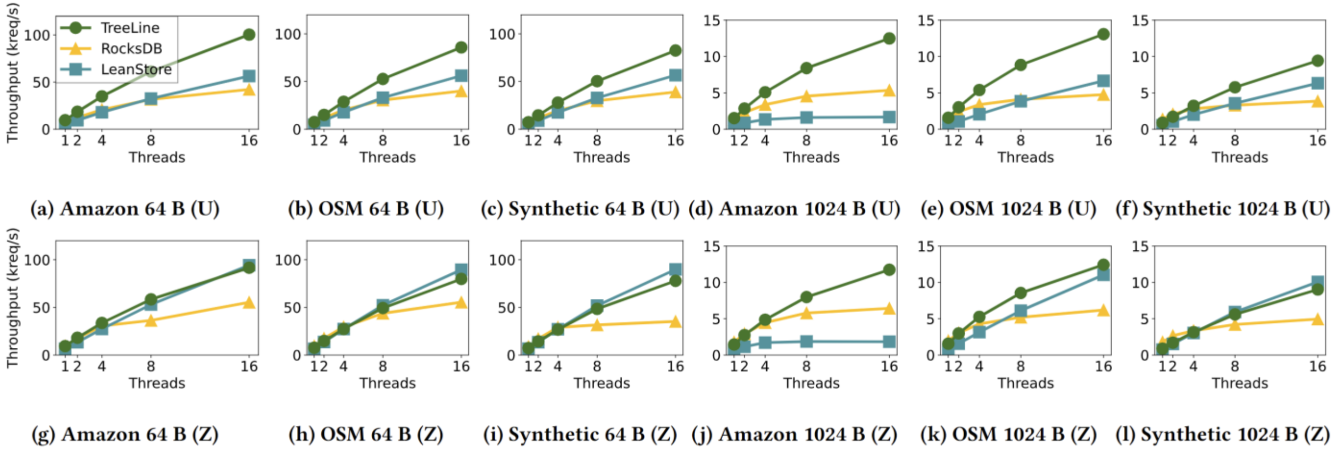
We look at throughput under parallelism



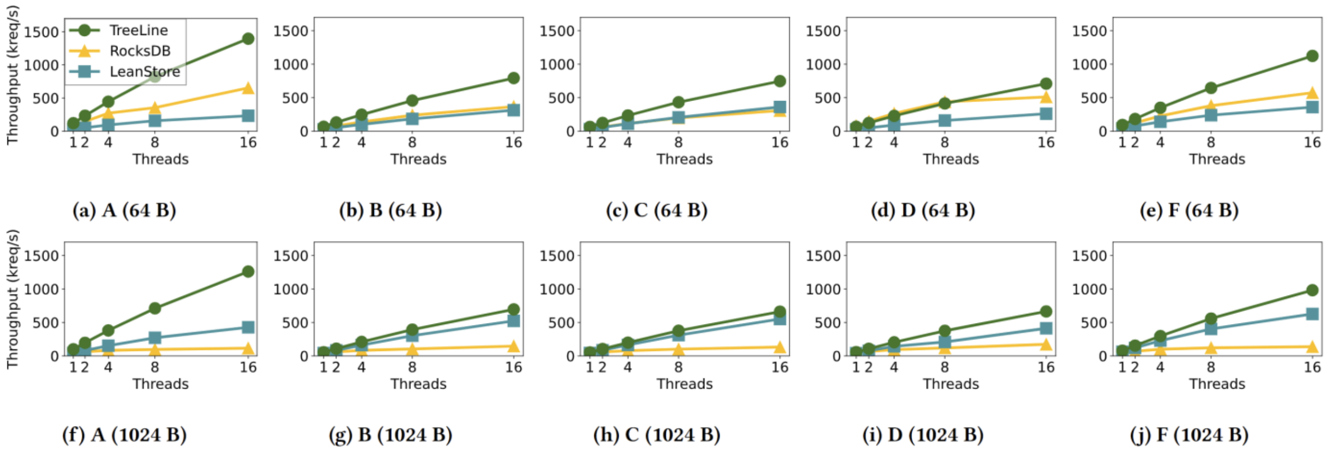
TreeLine shines across the board

- Only keep the high-level trends from here.
- We will dive deeper in the following slides.





Physical I/O drives the win over RocksDB

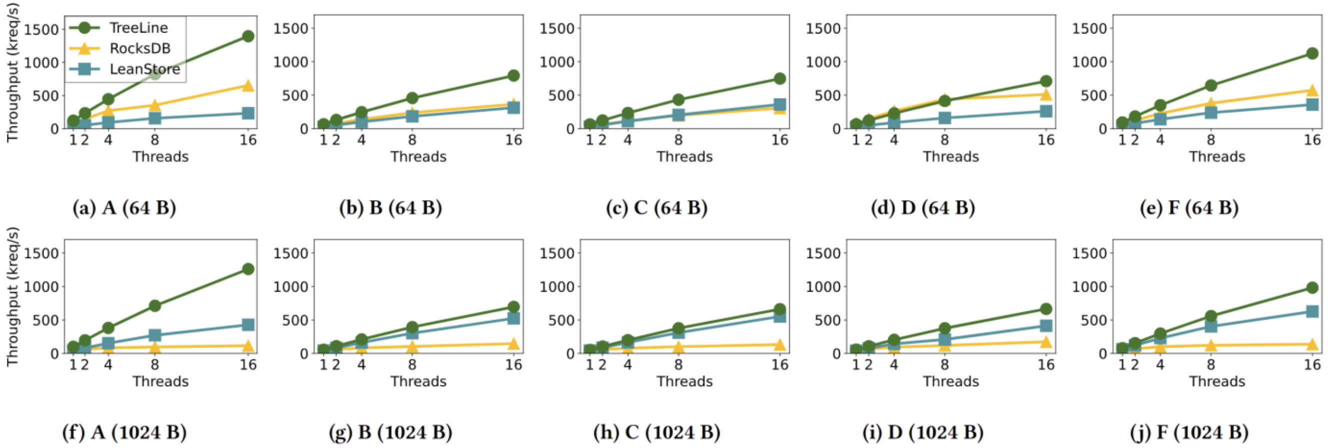


(a) A (64 B) (b) B (64 B) (c) C (64 B) (d) D (64 B) (e) F (64 B)

(f) A (1024 B) (g) B (1024 B) (h) C (1024 B) (i) D (1024 B) (j) F (1024 B)

- **Against RocksDB:** 1.62x for 64 B records, 2.99x for 1024 B records.
- **Case study:** Workload A (50% reads, 50% updates)
  - TreeLine writes 3.09 GiB physical data, RocksDB writes 4.27 GiB. Memtables cannot consolidate updates.
  - TreeLine reads 12 GiB physical data, RocksDB reads 27 GiB. RocksDB needs background compactions.
  - Same trend present for the rest of the point workloads.

Caching drives the win over LeanStore

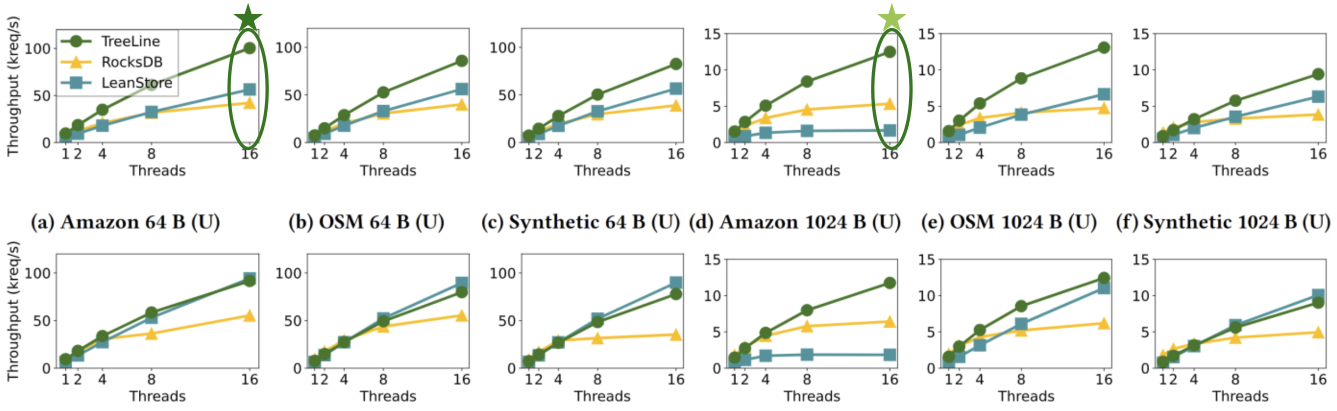


(a) A (64 B) (b) B (64 B) (c) C (64 B) (d) D (64 B) (e) F (64 B)

(f) A (1024 B) (g) B (1024 B) (h) C (1024 B) (i) D (1024 B) (j) F (1024 B)

- Same plots as last slide.
- **Against LeanStore:** 2.81x for 64 B records, 1.53x for 1024 B records.
- LeanStore caches pages, achieving worse cache utilization that again drives physical I/O up.
  - Notice how it outperforms RocksDB for 1024 B records, when the record size approaches the 4 KiB page size.

Update-in-place helps scans



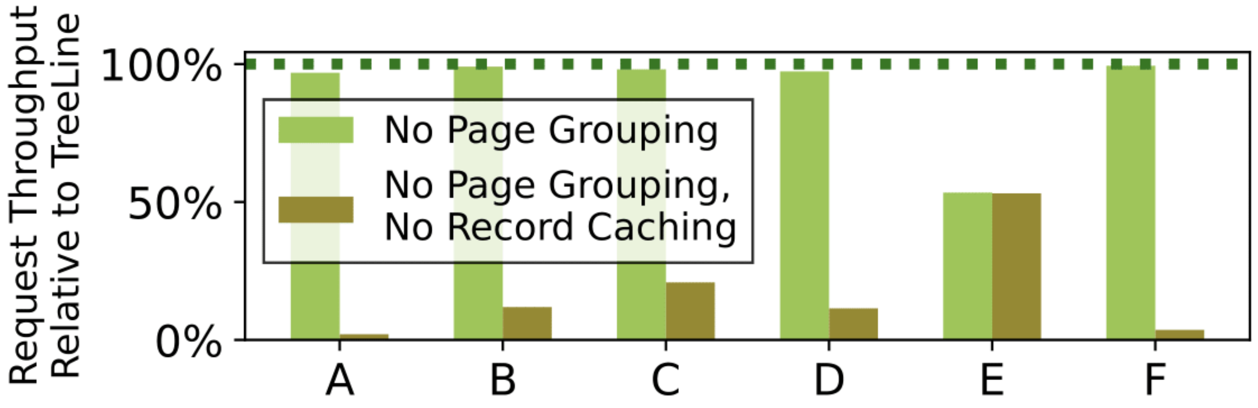
(a) Amazon 64 B (U) (b) OSM 64 B (U) (c) Synthetic 64 B (U) (d) Amazon 1024 B (U) (e) OSM 1024 B (U) (f) Synthetic 1024 B (U)

(g) Amazon 64 B (Z) (h) OSM 64 B (Z) (i) Synthetic 64 B (Z) (j) Amazon 1024 B (Z) (k) OSM 1024 B (Z) (l) Synthetic 1024 B (Z)

- TreeLine only stores one version of each record on disk.
- No need to merge results from different levels.
- Scan throughput (requests/second) outshines competition.
  - Less data to read than RocksDB.
  - Better throughput than LeanStore due to page grouping.

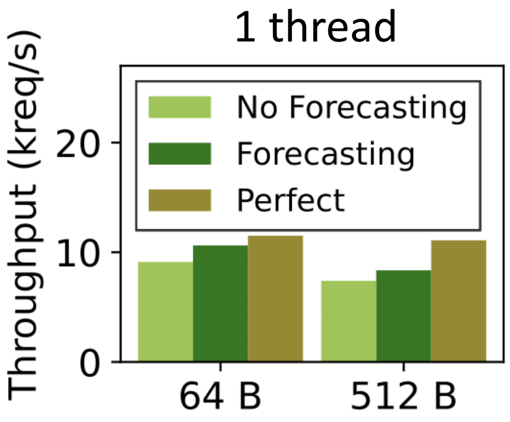
Config.	Phys. Reads	Phys. Read Thpt.	Req. Thpt.
TreeLine 64 B	**13.4 GiB**	550 MiB/s	**100 kreq/s**
RocksDB 64 B	31.1 GiB	**797 MiB/s**	42 kreq/s
LeanStore 64 B	17.0 GiB	581 MiB/s	56 kreq/s
TreeLine 1024 B	**75.9 GiB**	**1079 MiB/s**	**12 kreq/s**
RocksDB 1024 B	147 GiB	958 MiB/s	5.4 kreq/s
LeanStore 1024 B	76.4 GiB	155 MiB/s	1.7 kreq/s

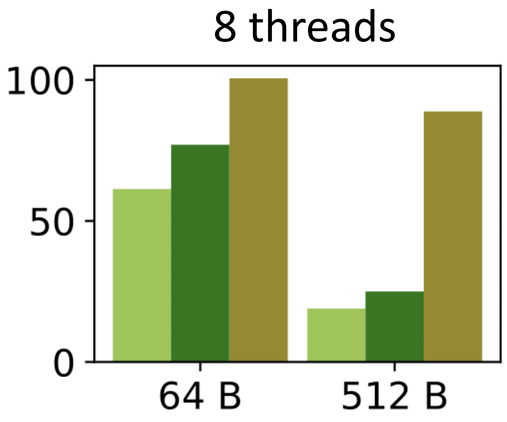
Caching & grouping are complementary

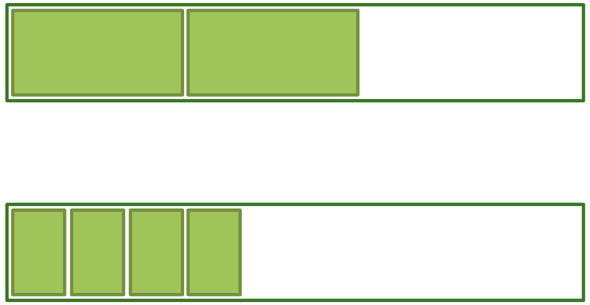


- For point workloads (A-D, F), record caching provides most of the benefit: keeping the hot working set in memory.
- For scan-heavy workload E, page grouping doubles the throughput.
- Grouping does not hurt point workload performance.

Forecasting inserts gives an extra boost

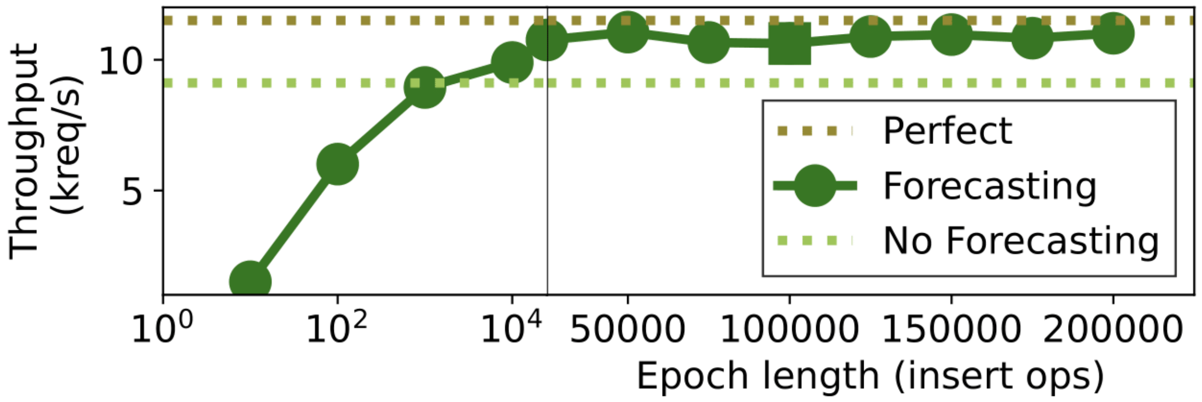






- Dataset: NYC taxi pickups (key is inlined location)
- 64B case: Closes more than half of the gap to perfect.
- 64B case: Reorganizations reduced by 63% on average (not plotted).
- 512B case: Not enough granularity on 4KiB page.
- Overall, improves base by 1.22x and reduces reorganizations by 41% on average.

Coarse-grained epoch tuning is enough



- Epoch length affects throughput.
- Small epochs: Can capture trends at small timescales, but lots of background work.
- Long epochs: Can get a more representative sample, but might “average out” some trends.
- Still, even an epoch length 1/10 or 2x of what we used in the paper would be an improvement over no forecasting.

Key takeaways

- NVMe SSDs: Parallel random writes ≈ sequential write performance
  - Opportunity to revisit KVS design
- TreeLine: Update-in-place with three key ideas
  - **Record caching:** Efficient memory use for skewed read/write workloads
  - **Page grouping:** Large physical reads for scans, single-page reads for point lookups
  - **Insert forecasting:** Proactively "leave space" for inserts
- Key results (YCSB throughput)
  - **Point workloads: 2.20x** and **2.07x** over RocksDB, LeanStore on average
  - **Uniform scan-heavy (16 threads): 2.50x** and **2.80x** over RocksDB, LeanStore
  - Up to **10.95x** and **7.52x** over RocksDB, LeanStore overall

Paper: tinyurl.com/treeline-paper