

SpanDB: A Fast, Cost-Effective LSM-tree Based KV Store on Hybrid Storage

Hao Chen^{1, 2}, Chaoyi Ruan¹, Cheng Li¹, Xiaosong Ma², Yinlong Xu^{1, 3}

¹ University of Science and Technology of China

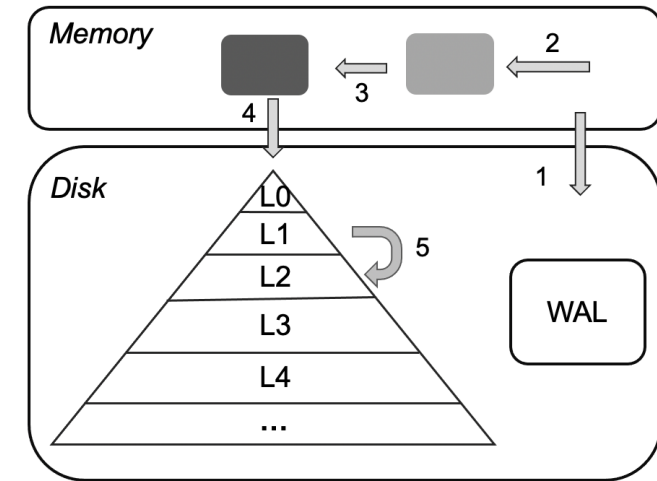
² Qatar Computing Research Institute, HBKU

³ Anhui Province Key Laboratory of High Performance Computing



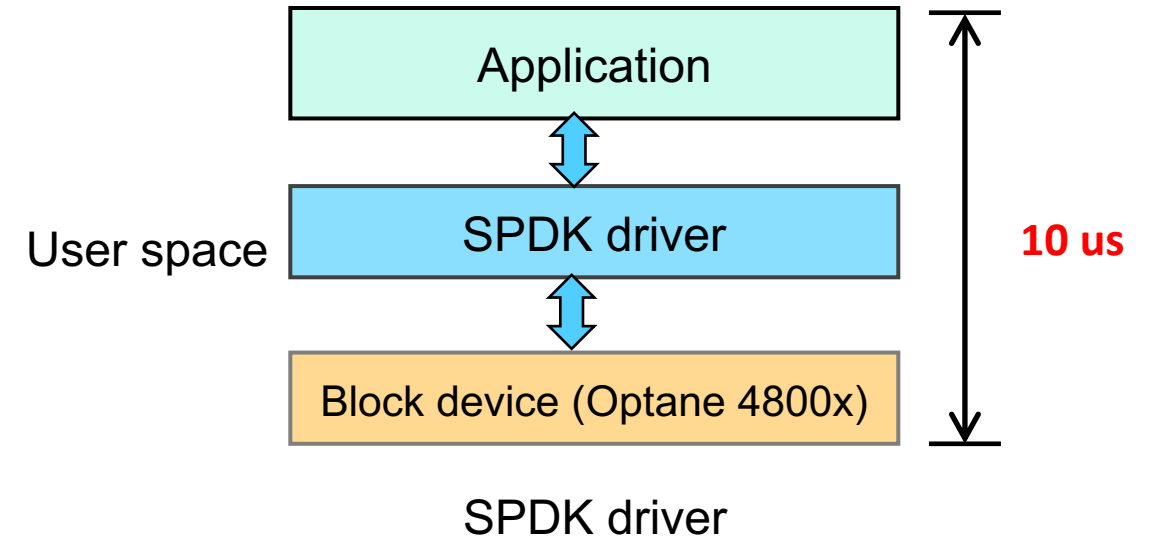
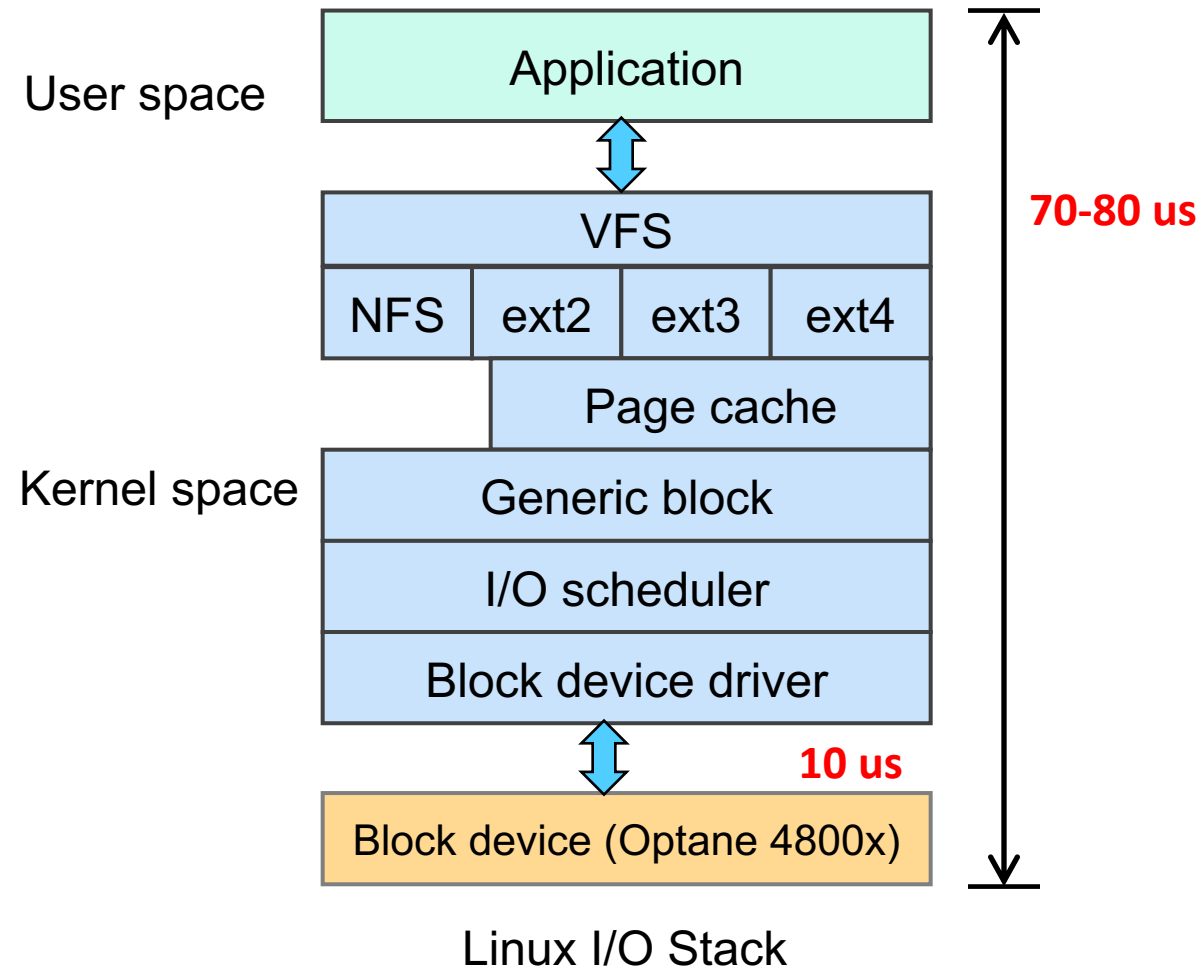
Rise of Key-Value Stores

- ❑ Persistent key-value (KV) stores popular and important
 - ❖ Storing semi-structured data for enterprise services
 - E.g., **LevelDB** by Google, **RocksDB** by Facebook
 - ❖ Being backend storage engine for
 - **Ceph**, **MyRocks**, **TiDB**, **Cassandra**
 - ❖ **LSM-tree** based KV stores are popular
- ❑ Opportunities for performance enhancement brought by high-end **NVMe** storage devices



- ❑ **Unfortunately, their potential not fully exploited by modern LSM-tree based KV stores**

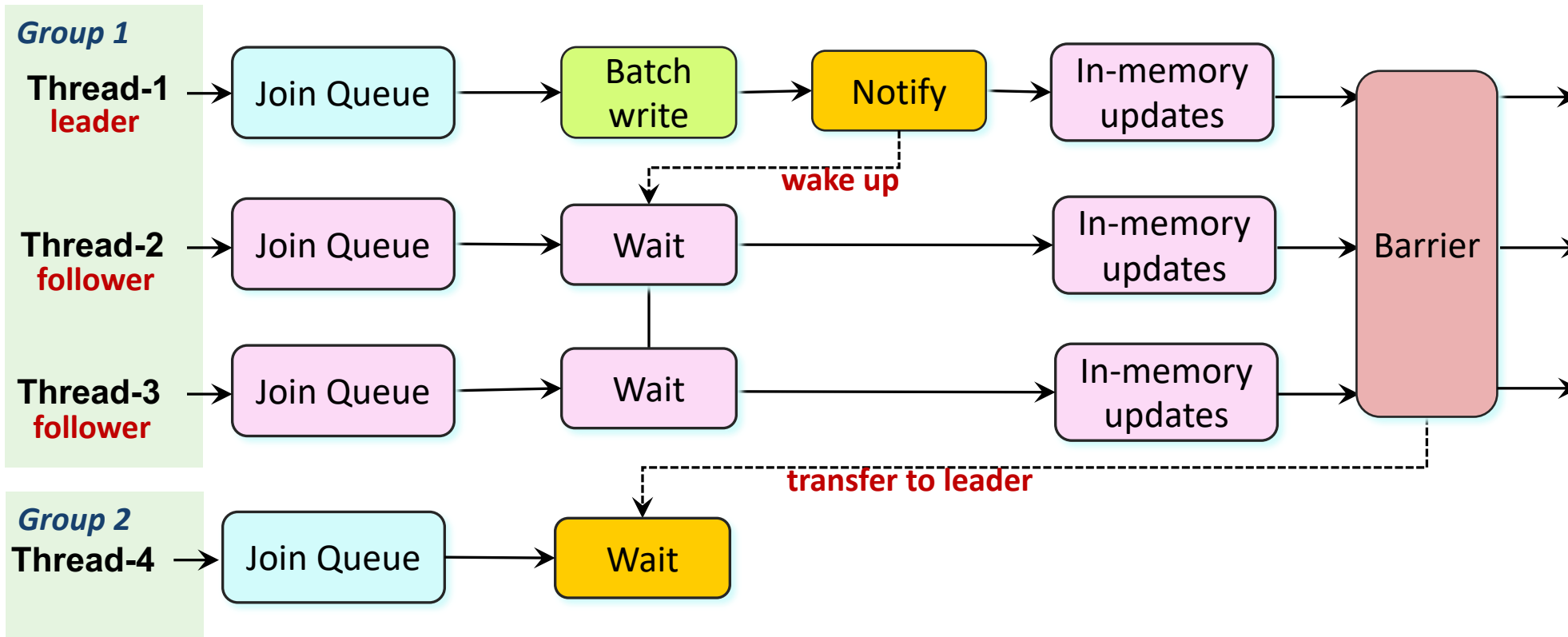
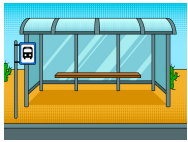
Challenge 1: Fast Accesses to Fast Devices



- ❑ Lower latency stemming from
 - ❖ User-space driver, avoid syscall
 - ❖ Polling for completion rather than interruption
- ❑ However, benefits come at costs
 - ❖ Need to manage raw space with **no FS support**
 - ❖ Busy wait wastes CPU cycles

Challenge 2: Thread Sync Overhead in Group Logging

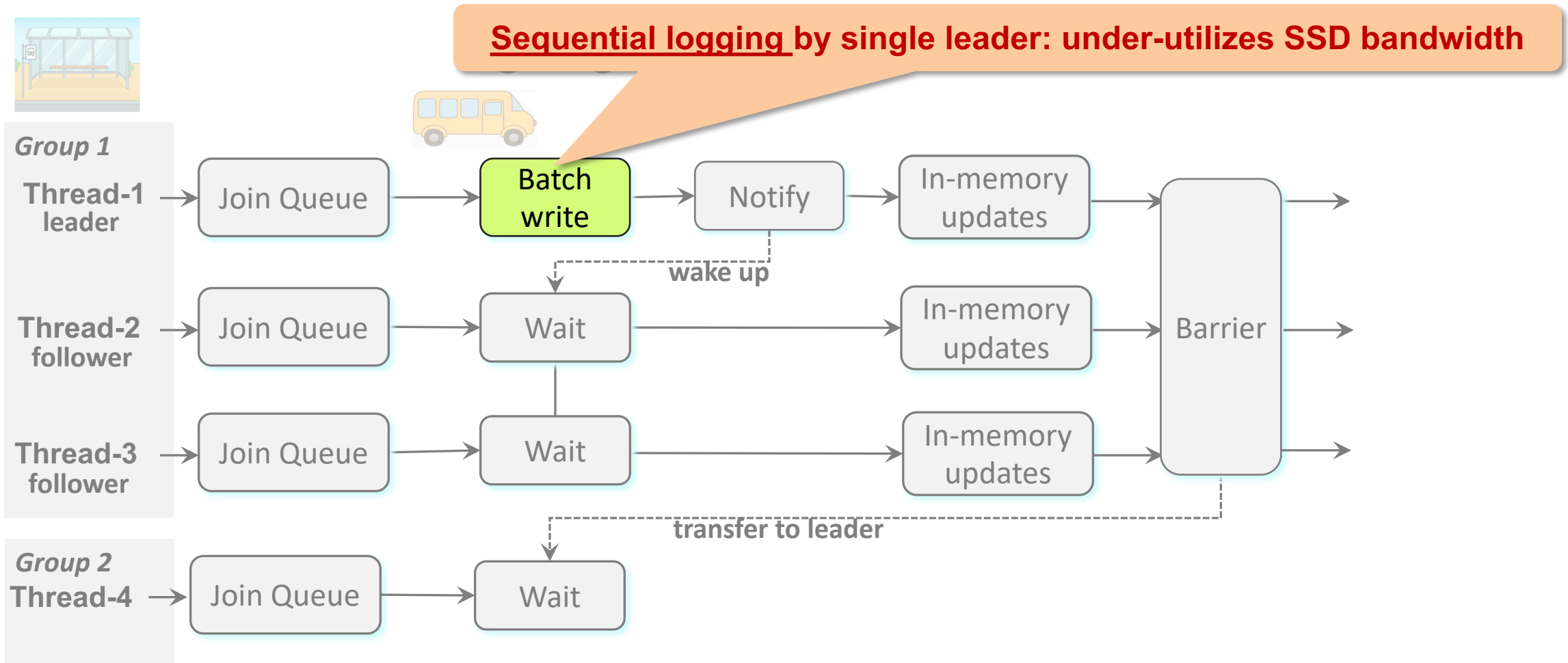
- ❑ **Group logging**: widely used to speed up write-ahead logging (WAL)
- ❑ All existing group logging implementations **sequential**



RocksDB/LevelDB group logging process

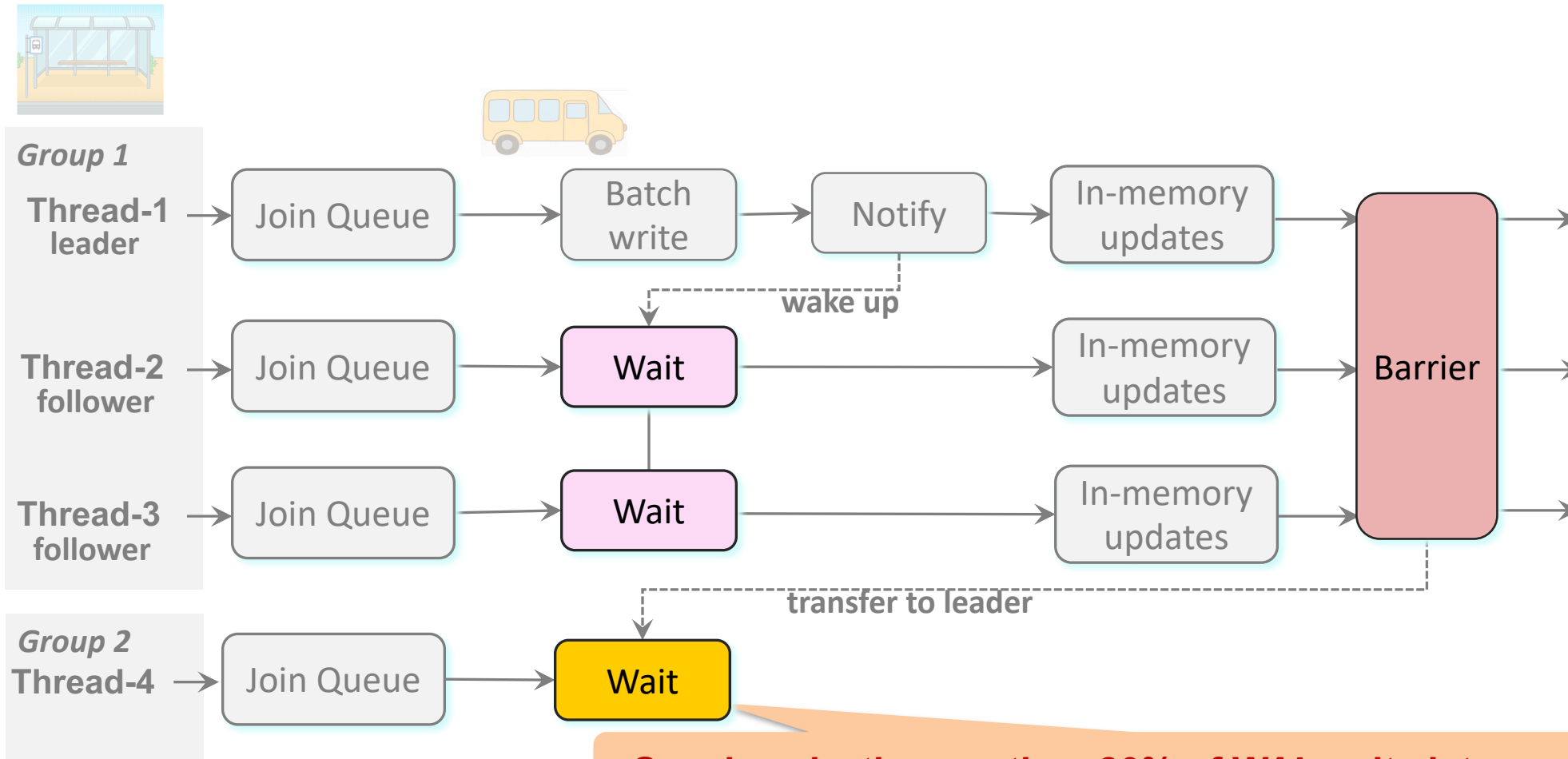
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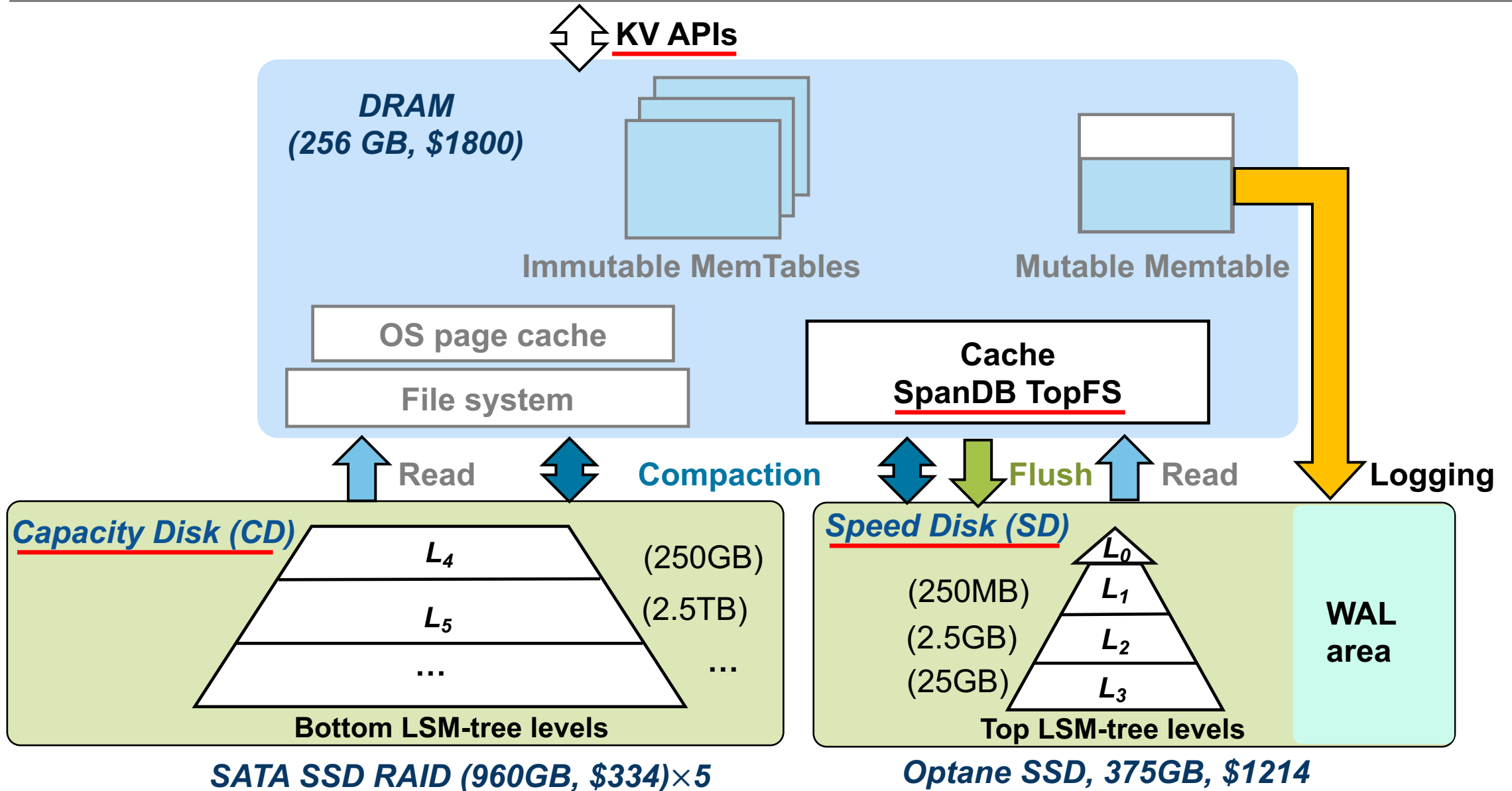


Synchronization costly: >80% of WAL write latency on Optane SSD

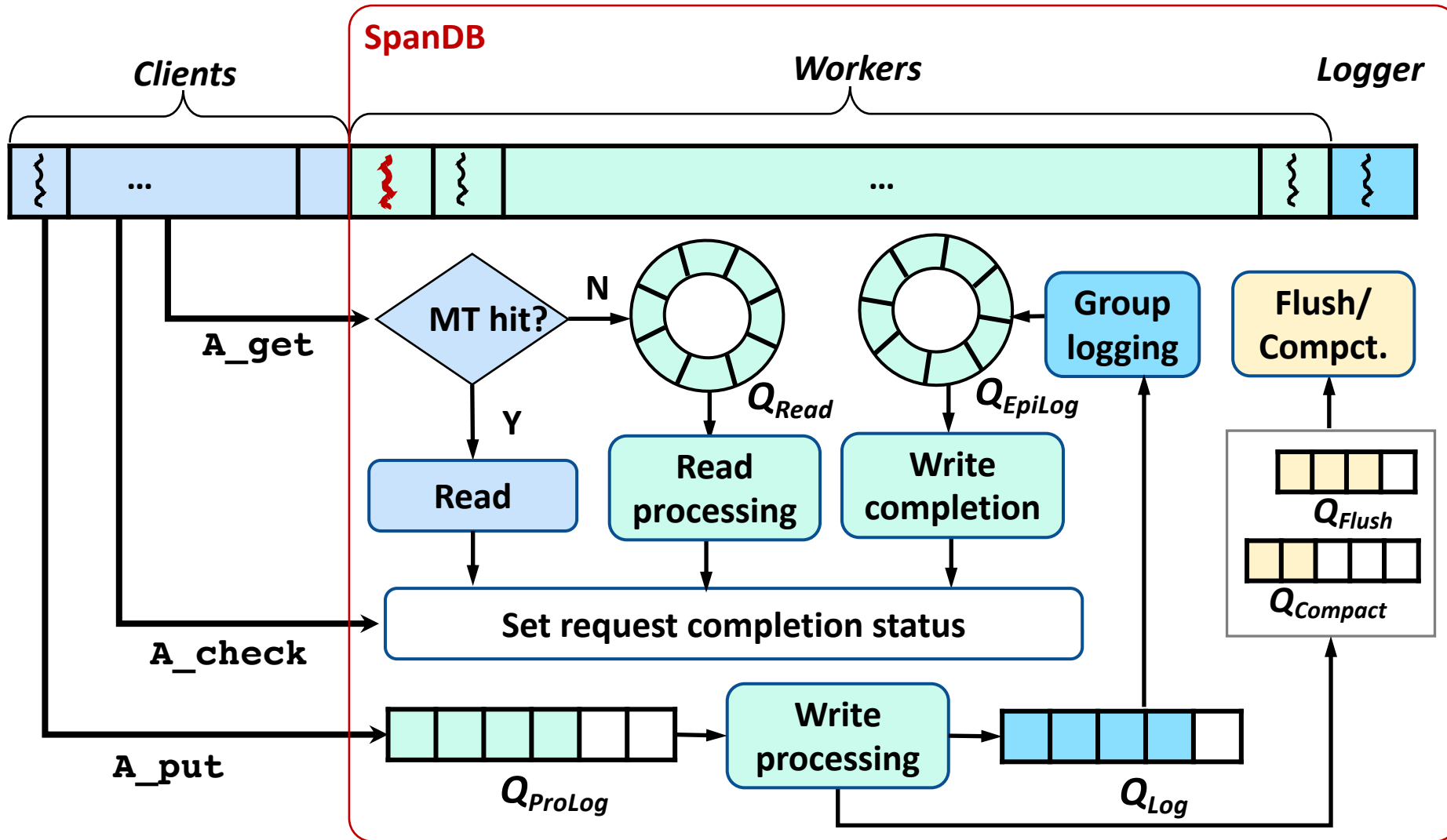
Related Work and Our Approach

- ❑ Optimized KV stores based on LSM-tree
 - ❖ [PebblesDB](#) [SOSP'17], [SILK](#) [ATC'19], [ElasticBF](#) [ATC'19], [SplinterDB](#) [ATC'20]
 - ❖ Limitations: data structure changes, using conventional Linux I/O stack
- ❑ Develop KV stores on NVMe SSDs
 - ❖ [KVSSD](#) [SYSTOR'19], [KVell](#) [SOSP'19], [FlatStore](#) [ASPLOS'20]
 - ❖ Limitations: High hardware cost, loss of transaction support in some cases
- ❑ **Our focus and major approach**
 - ❖ **Cost-effectiveness**: coupling small, fast devices with larger, slower ones
 - ❖ **Full utilization of fast device**: latency, bandwidth, and capacity
 - ❖ **Compatibility**: enhancing widely used RocksDB, no new data structures

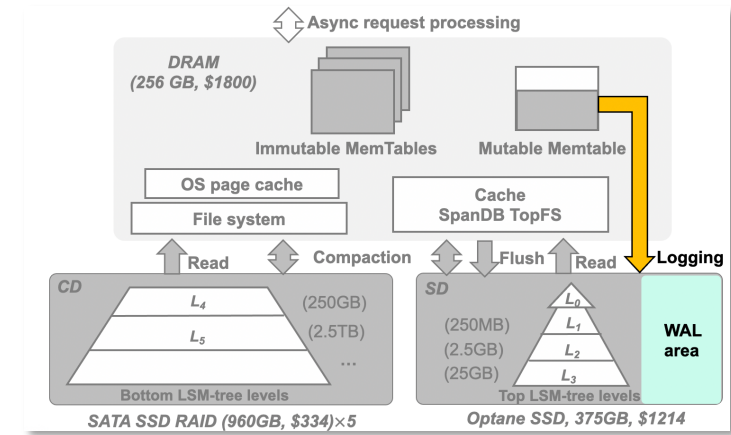
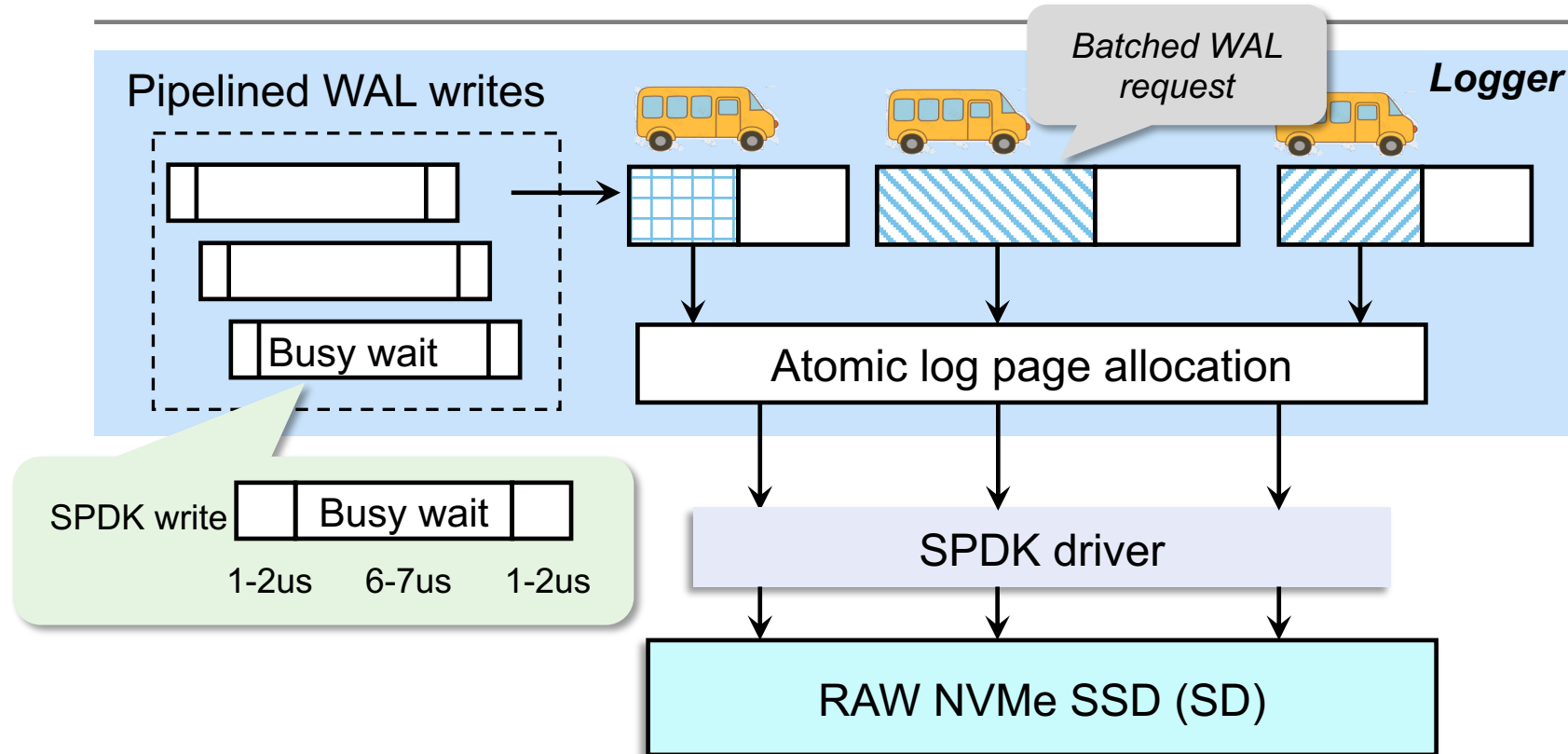
SpanDB Overview



Async. KV Request Processing

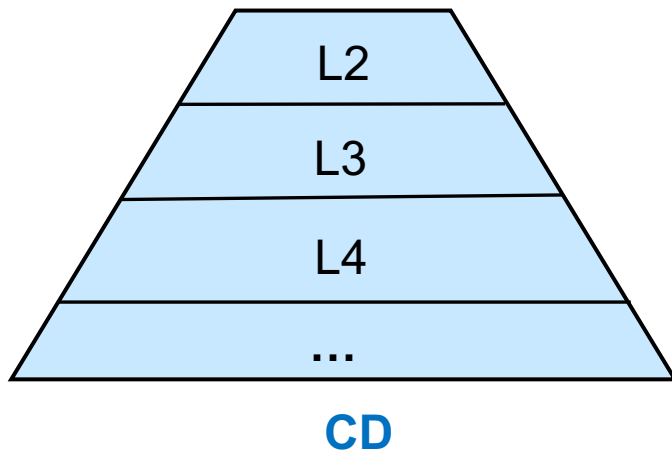


Parallel Logging via SPDK

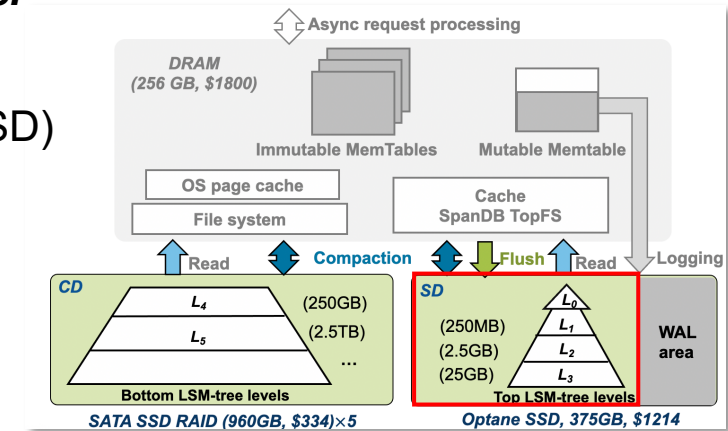
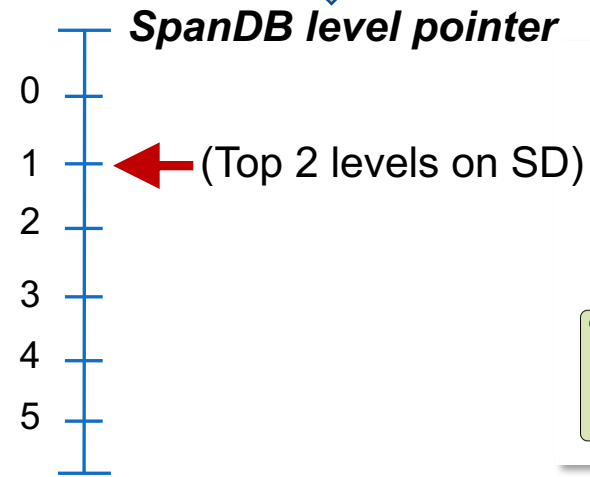
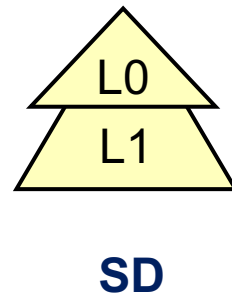


- ❑ WAL writes to log area on raw device via SPDK
 - ❖ **Concurrent:** for better NVMe device utilization
 - ❖ **Pipelined:** for better CPU time utilization busy
 - ❖ 1-2 dedicated loggers able to saturate Optane
 - ❖ Additional metadata management for consistency without FS

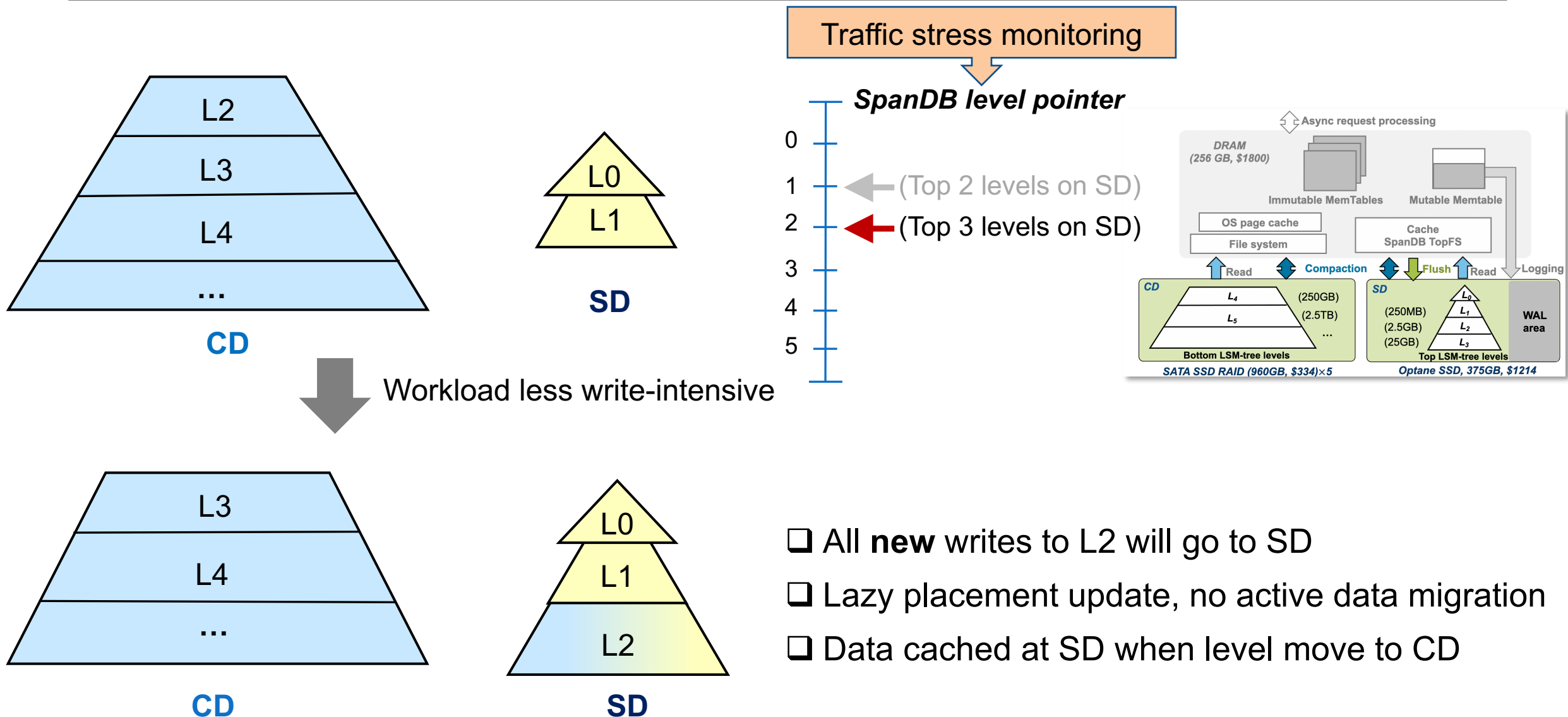
Dynamic LSM-Tree Level Placement



Workload less write-intensive



Dynamic LSM-Tree Level Placement



Experimental Setup

❑ Hardware

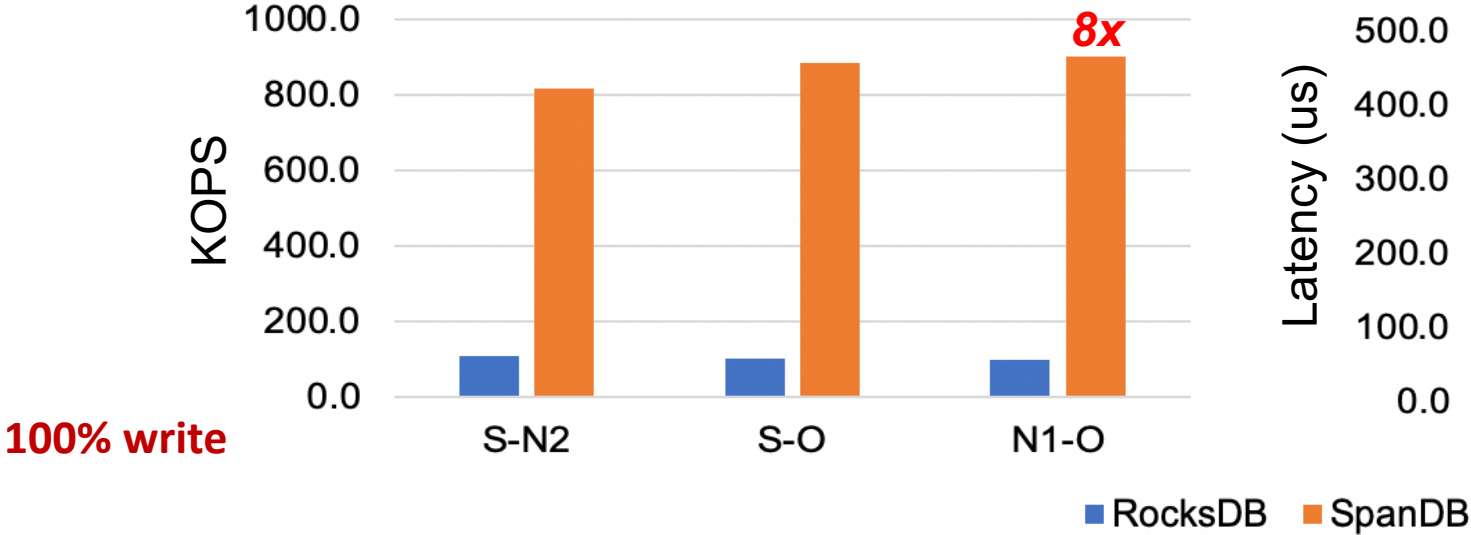
- ❖ 2 20-core CPUs, 256GB memory
- ❖ 4 types of **data center** storage devices

ID	Model	Price	Seq. write bandwidth	Write latency
S	Intel S4510 (SATA)	0.26 \$/GB	510 MB/s	37 us
N1	Intel P4510 (NVMe)	0.25 \$/GB	2900 MB/s	18 us
N2	Intel P4610 (NVMe)	0.40 \$/GB	2080 MB/s	18 us
O	Intel Optane P4800X (NVMe)	3.25 \$/GB	2000 MB/s	10 us

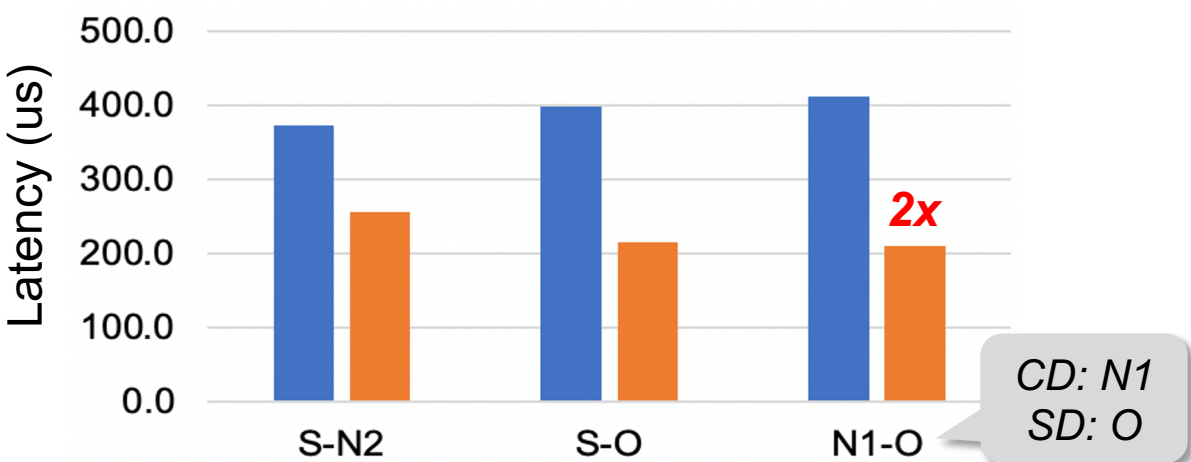
- ❑ Workloads: **YCSB** and **LinkBench**
- ❑ Baselines: **RocksDB** (v6.5.1), **KVell** [SOSP'19], and **RocksDB-BlobFS**
- ❑ Database size: primarily with **512GB**, up to **2TB**

YCSB Results, Comparison w. RocksDB

Throughput (the higher, the better)

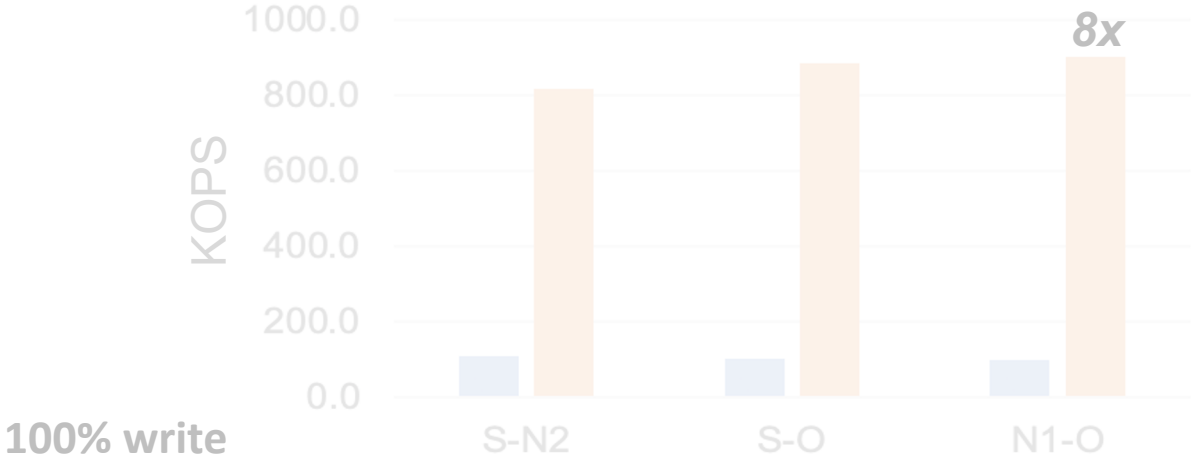


Latency (the lower, the better)

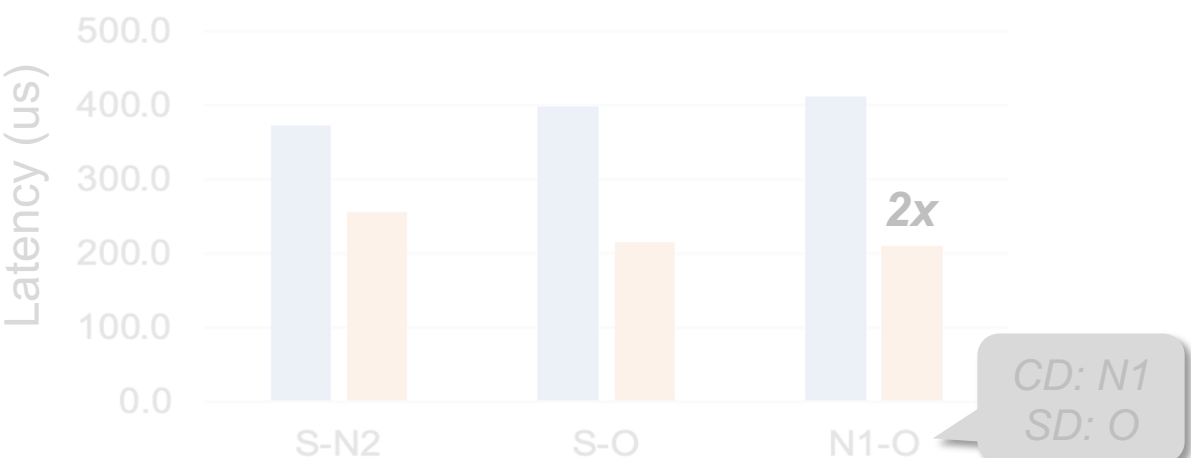


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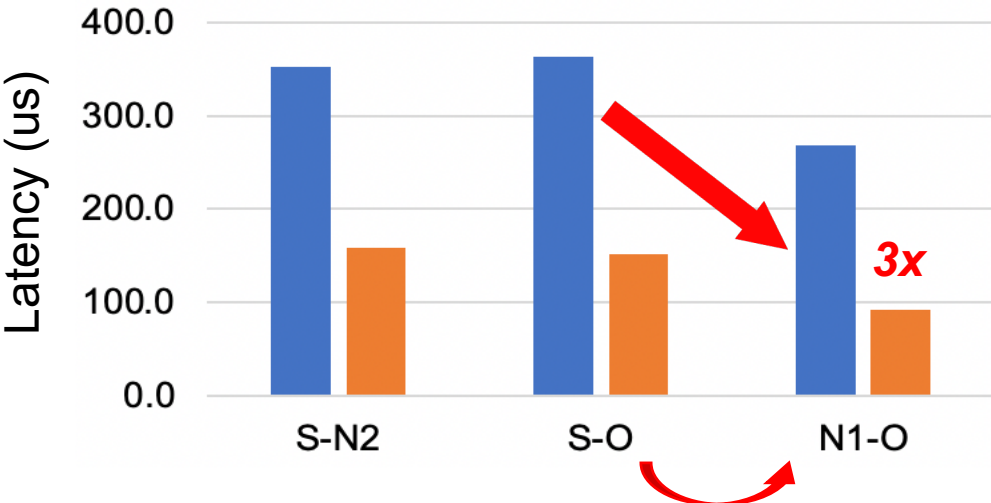
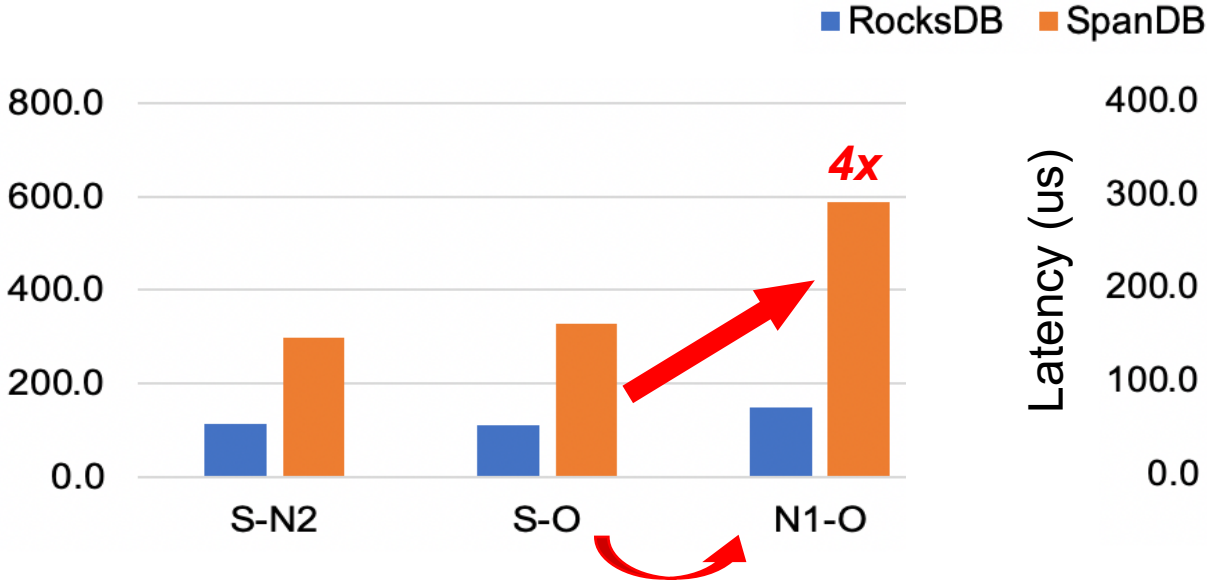
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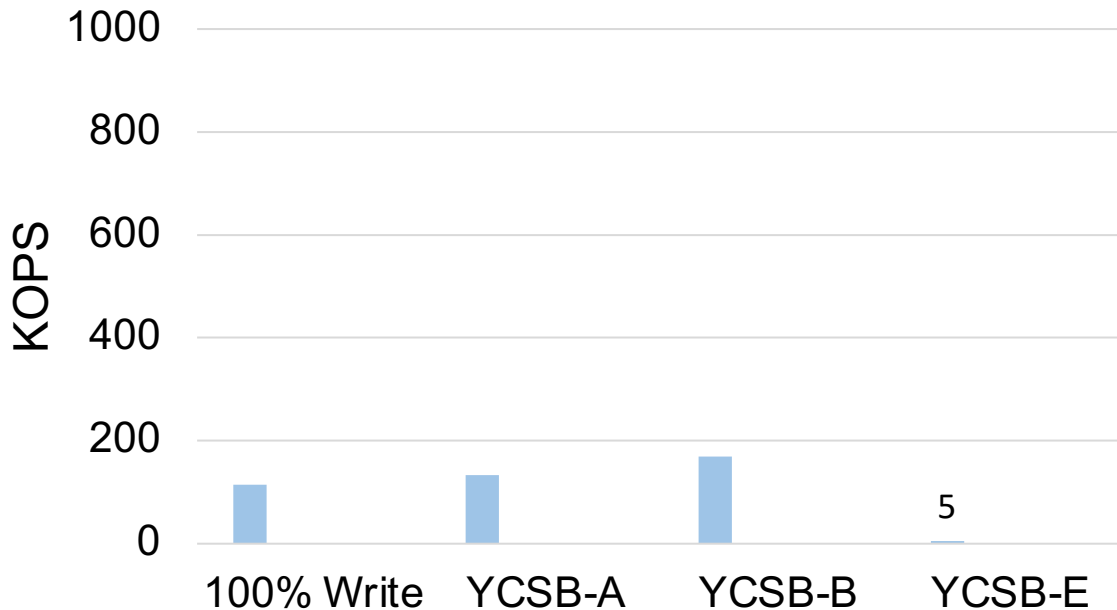
YCSB-A
50% update
50% read



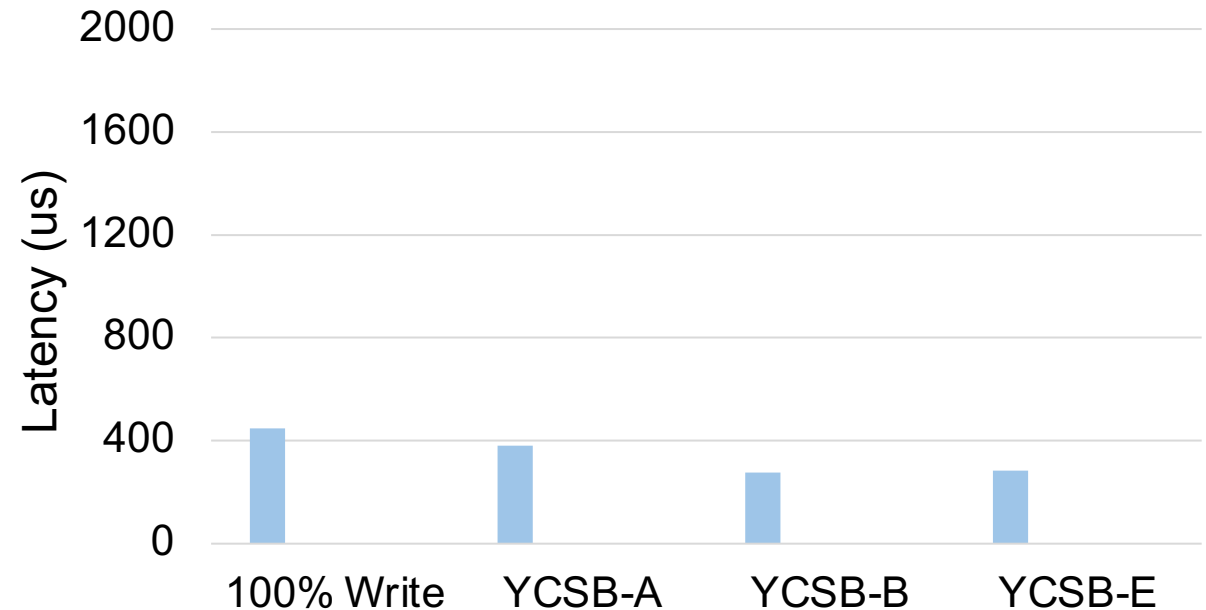
YCSB Results, Comparison w. KVell

KVell (N1-N1) (B=1)

Throughput (the higher, the better)



Latency (the lower, the better)

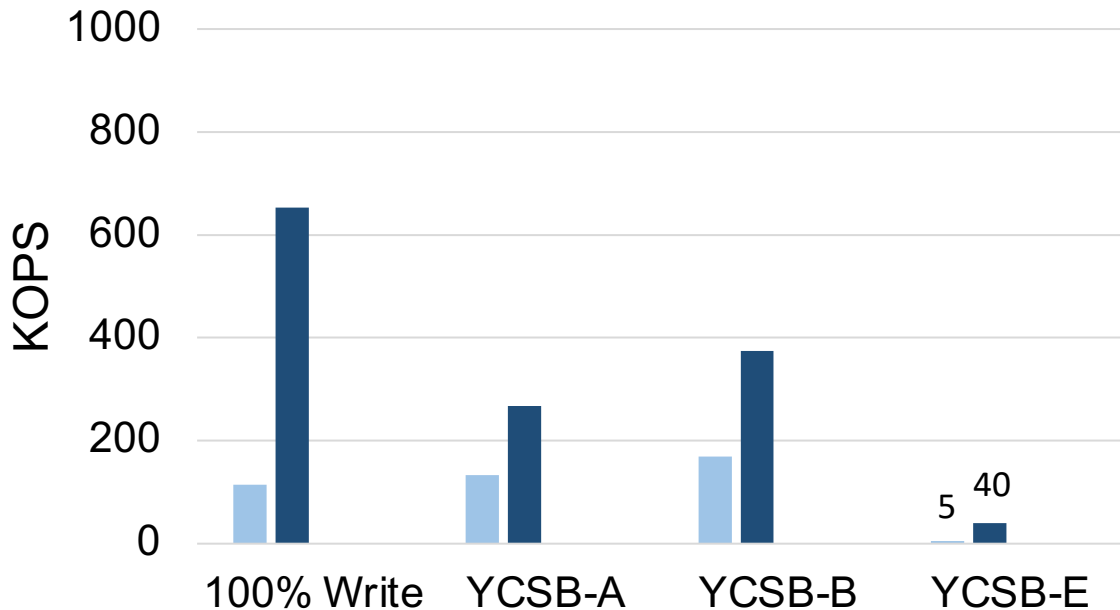


- ❑ 2TB database
- ❑ YCSB-A: 50% update and 50% read, YCSB-B: 5% update and 95% read, YCSB-E: 5% update and 95% scan
- ❑ KVell (B=1): batch size = 1 in KVell

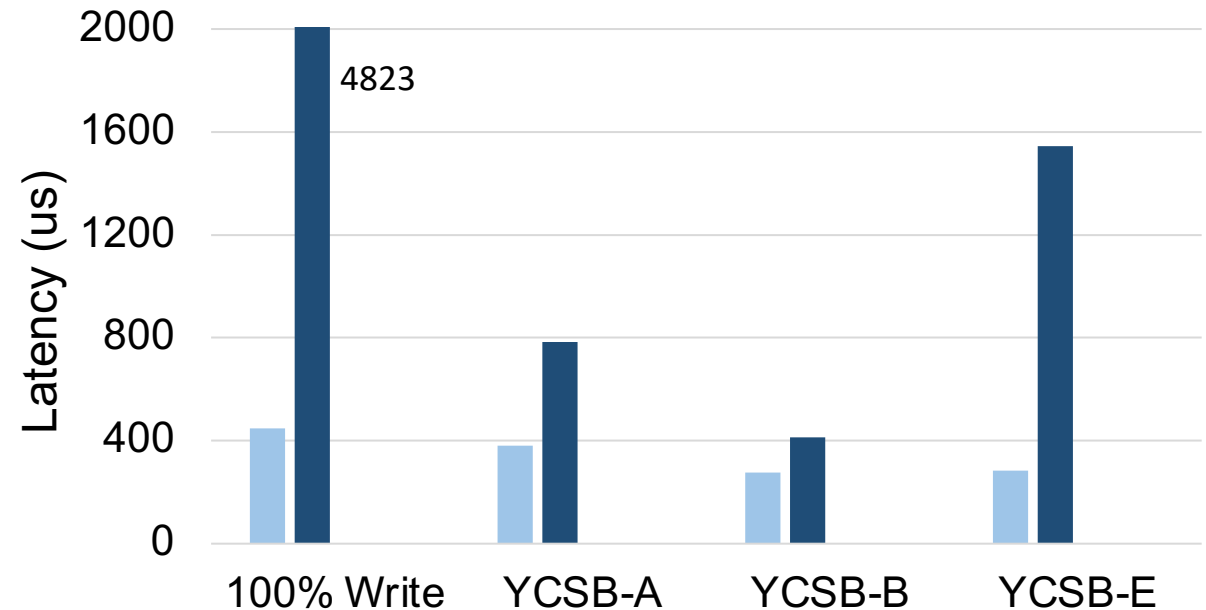
YCSB Results, Comparison w. Kvell

■ Kvell (N1-N1) (B=1) ■ Kvell (N1-N1) (B=match)

Throughput (the higher, the better)



Latency (the lower, the better)

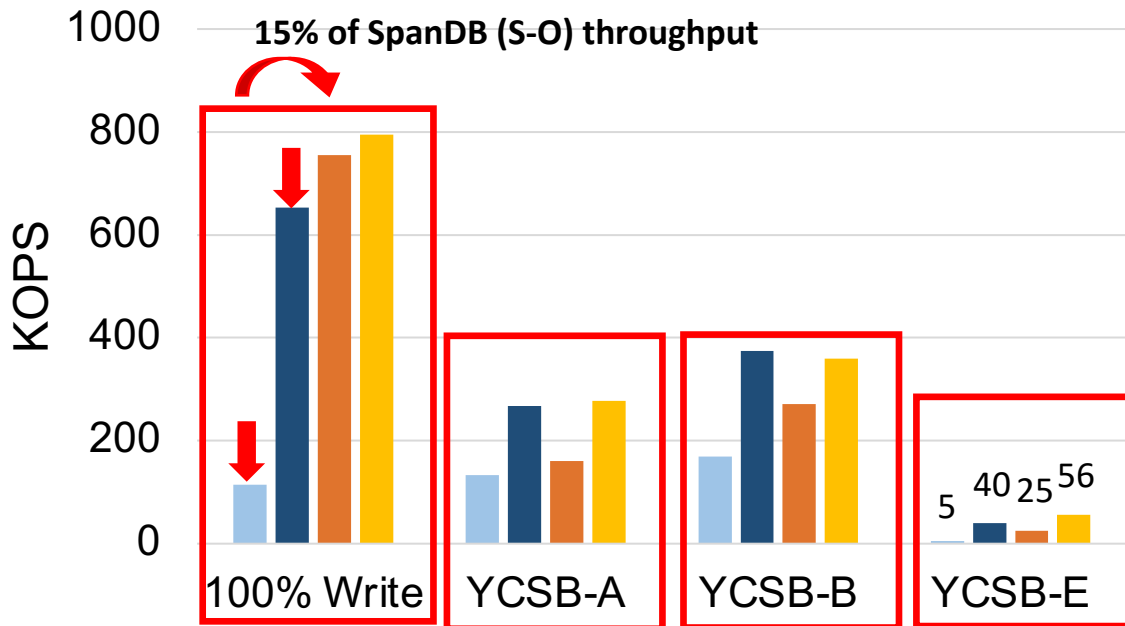


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- ❑ Kvell (B=1): batch size = 1 in Kvell
- ❑ Kvell (B=match): the smallest batch size that surpasses SpanDB's throughput

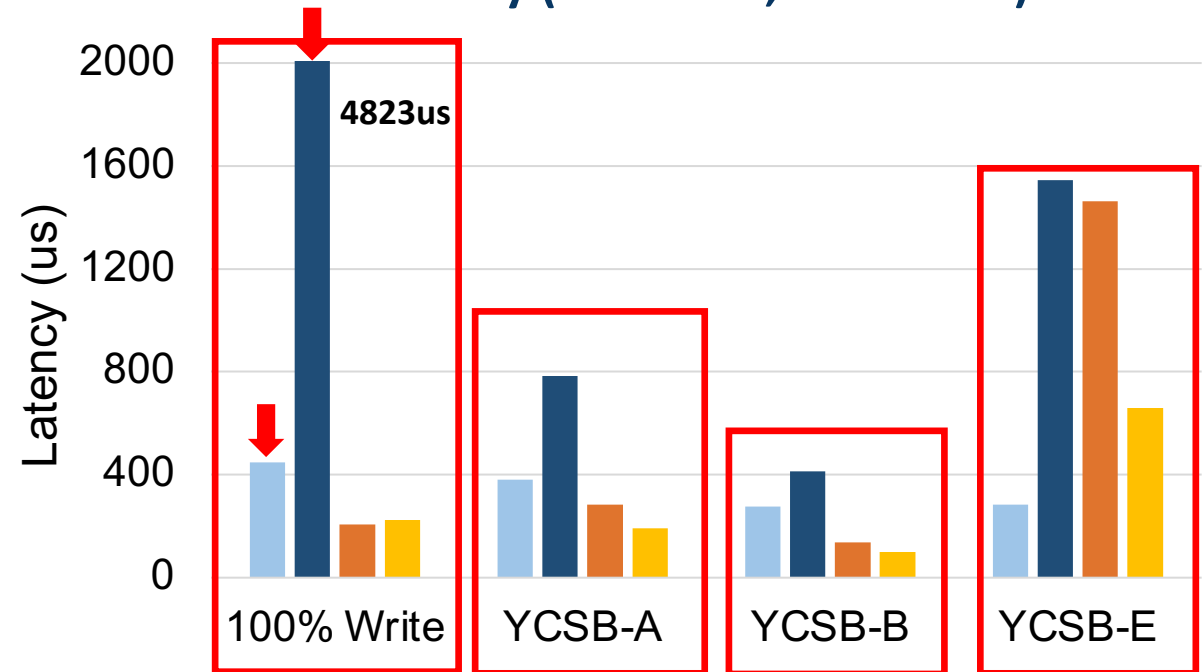
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Open-source: <https://github.com/SpanDB/SpanDB>

Thanks

{cighao, rcy}@mail.ustc.edu.cn, {chengli7, ylxu}@ustc.edu.cn, xma@hbku.edu.qa