BOSTON UNIVERSITY

ENDURE: A Robust Tuning Paradigm for LSM Trees Under Workload Uncertainty

Andy Huynh, Harshal A. Chaudhari, Evimaria Terzi, Manos Athanassoulis

Age of LSM trees

The LSM Tuning Problem



DRAM



Tree



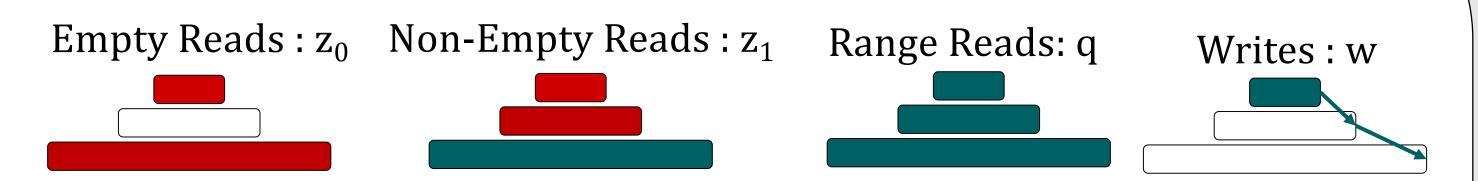
Disk

Flexibility for applications



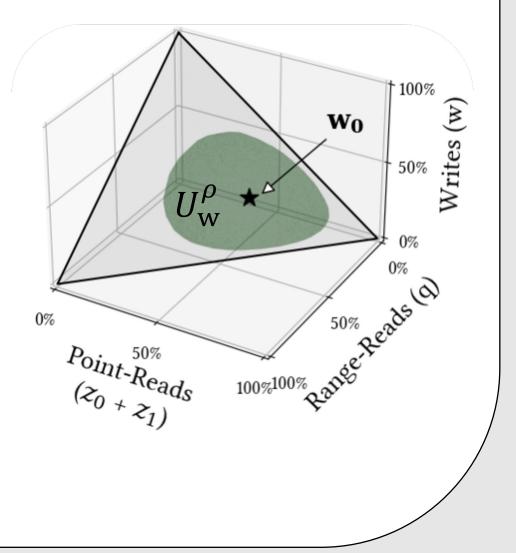
Size Ratio **Buffer Size** Compaction High impact tuning knobs

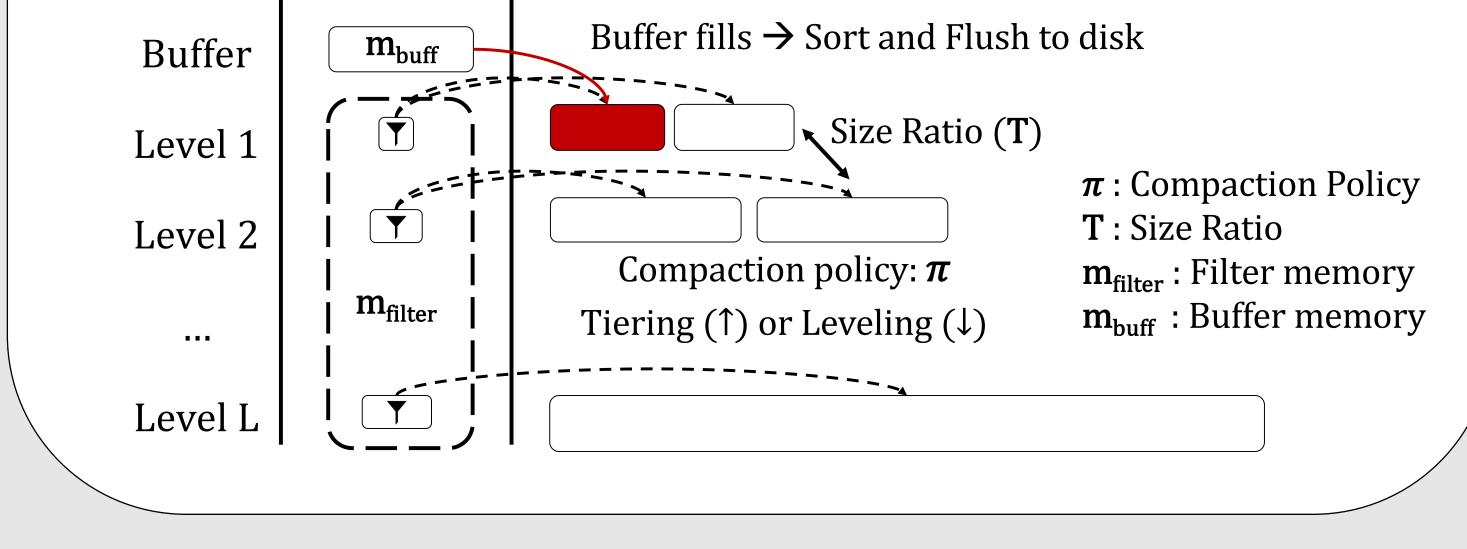
Cost is sum of expected I/Os per query type, weight by frequency



Both problems are finding the design Φ that minimizes *C*. **Nominal** bases decision on w, while **Robust** considers all workloads in U_w^{ρ}

w: Workload (z_0, z_1, q, w)





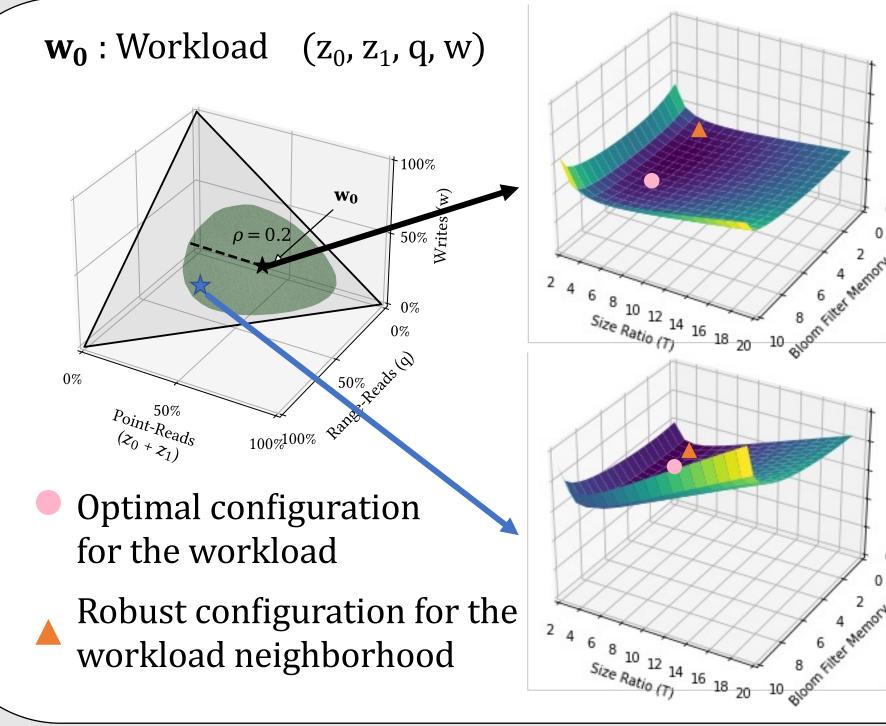
 Φ : LSM Tree Design $(m_{buff}, m_{filter}, T, \pi)$ *C* : Cost (I/O)

> $\Phi^* = \operatorname{argmin}_{\Phi} \mathcal{C}(\boldsymbol{w}, \Phi)$ Nominal

 $U_{\rm w}^{\rho}$: Uncertainty neighborhood of workloads ρ : Size of this neighborhood

> $\Phi^* = \operatorname{argmin}_{\Phi} C(\widehat{w}, \Phi)$ $\widehat{\boldsymbol{w}} \in U_w^{\rho}$ s.t.,

The LSM Tuning Problem



Nominal tuning may lead to suboptimal tunings if observed workloads and expected workloads are **far**

Robust tuning solution minimizes **highest** value among **any** workload in our uncertainty neighborhood

Uncertainty neighborhood

ENDURE: Robust Tuning

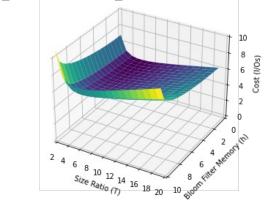
Workload Characteristic

System Information

Robust

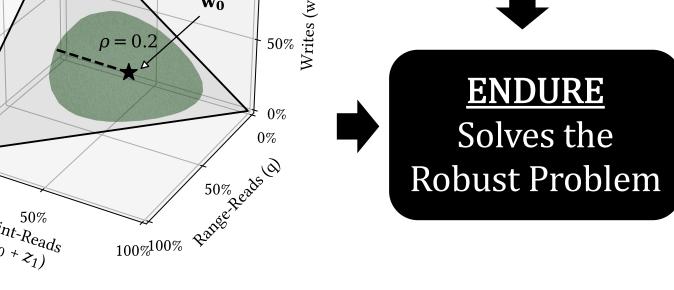
Expected performance

Page Size



RocksDB Configuration

Memory Budget

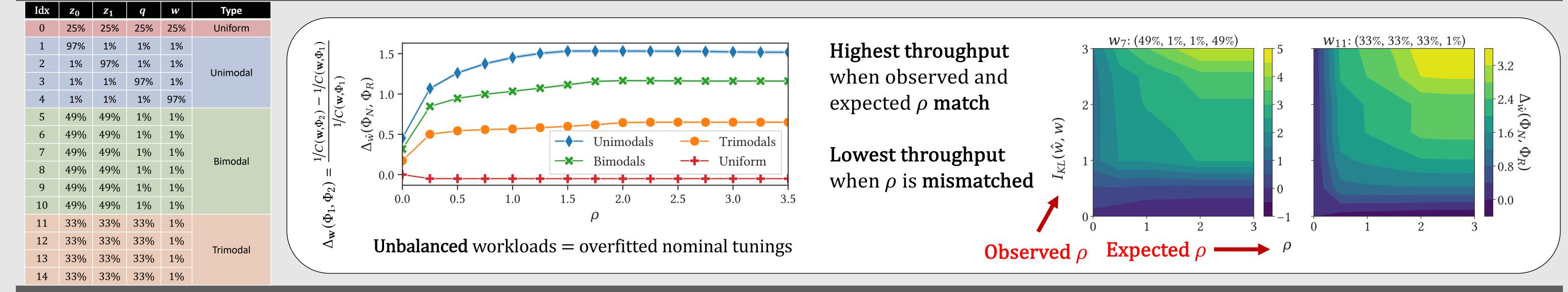


defines which workloads to consider for robust tuning

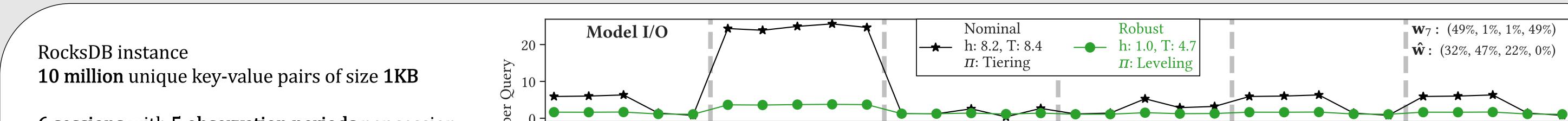
ENDURE implemented in Python **alongside RocksDB**

Users provide workload characteristics: expected workload and uncertainty

Selected Results (More can be found in our full paper)



Selected Results



6 sessions with 5 observation periods per session **Observation period:** 200K queries Overall **6million** queries

Writes are unique Range queries are short range queries (1-2 pages)

Small subset of results! Take a look at our paper for a more detailed analysis

