Adaptive Hybrid Indexes

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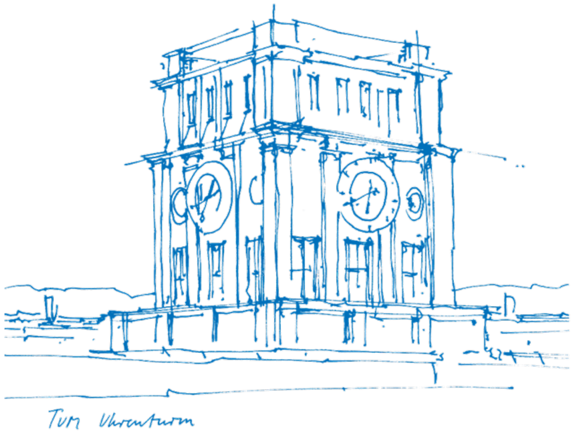
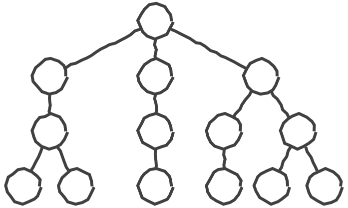
[3]Tsinghua University, China



Problem

Index structures are essential for fast query processing



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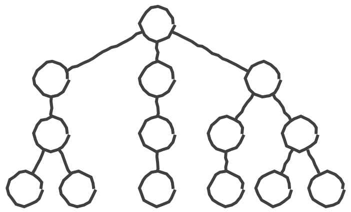
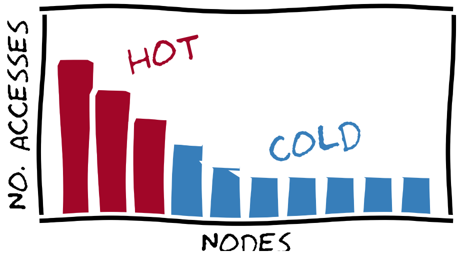


Real-world workloads have skew



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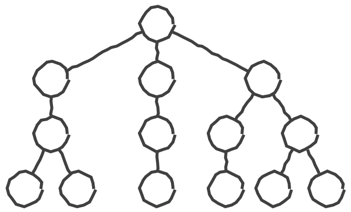

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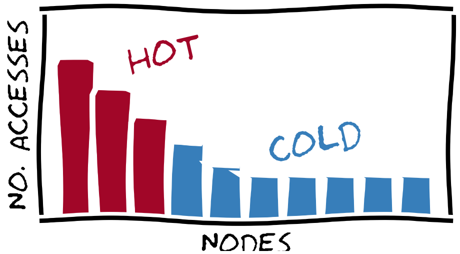

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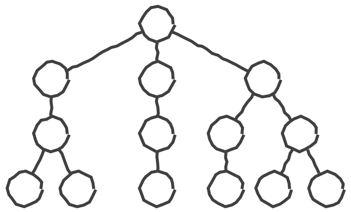

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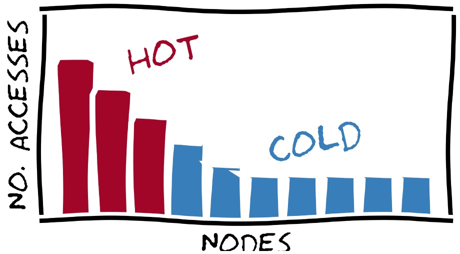

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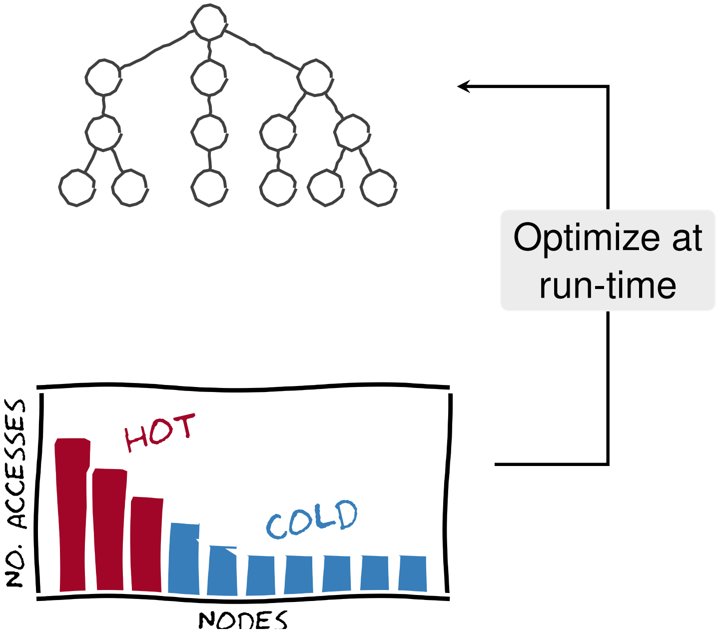

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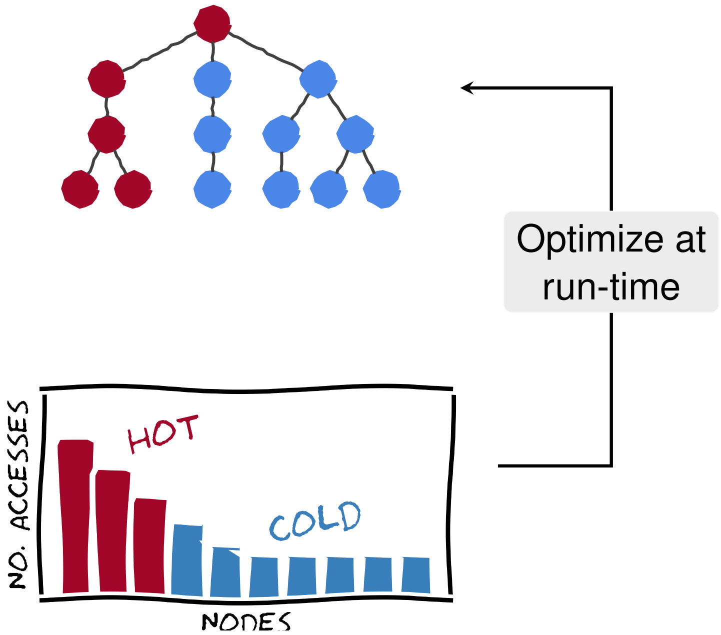
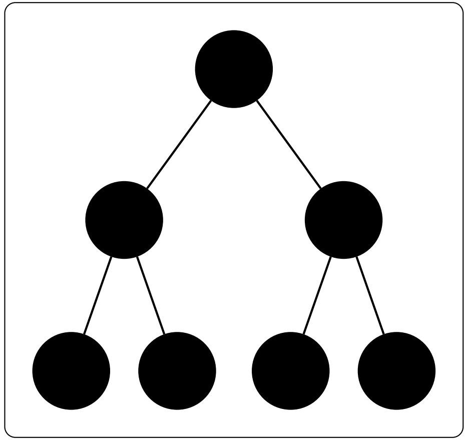


Solution

Adaptive Hybrid Index

Index Structure



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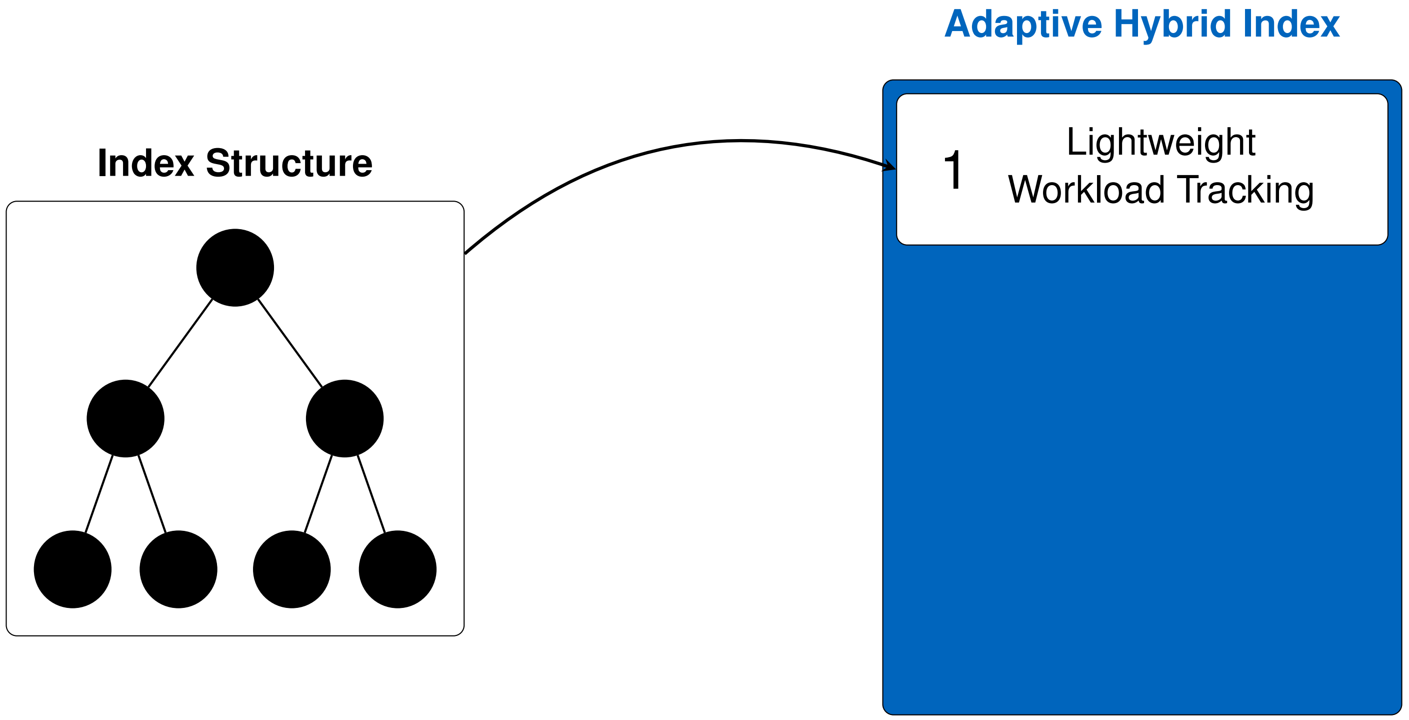
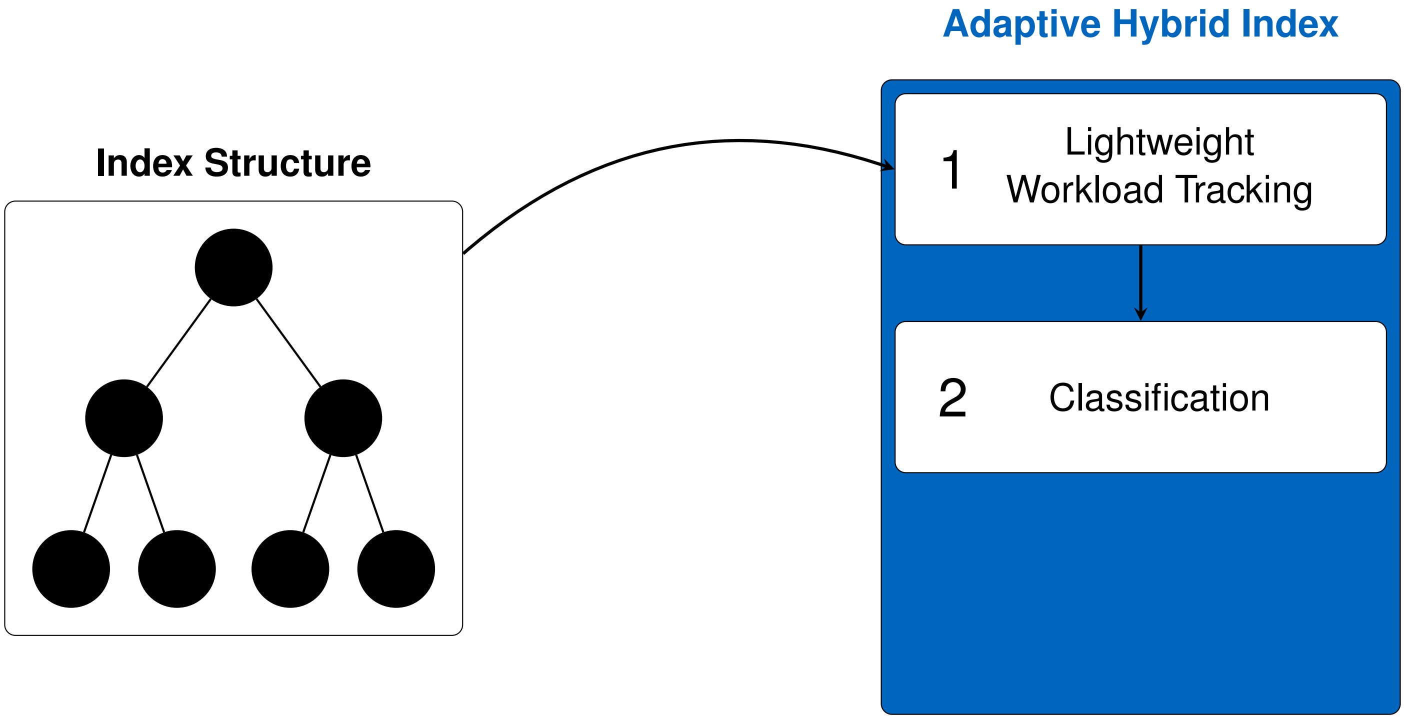

Adaptive Hybrid Index
Index Structure
1
Lightweight Workload Tracking

Solution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2 Classification

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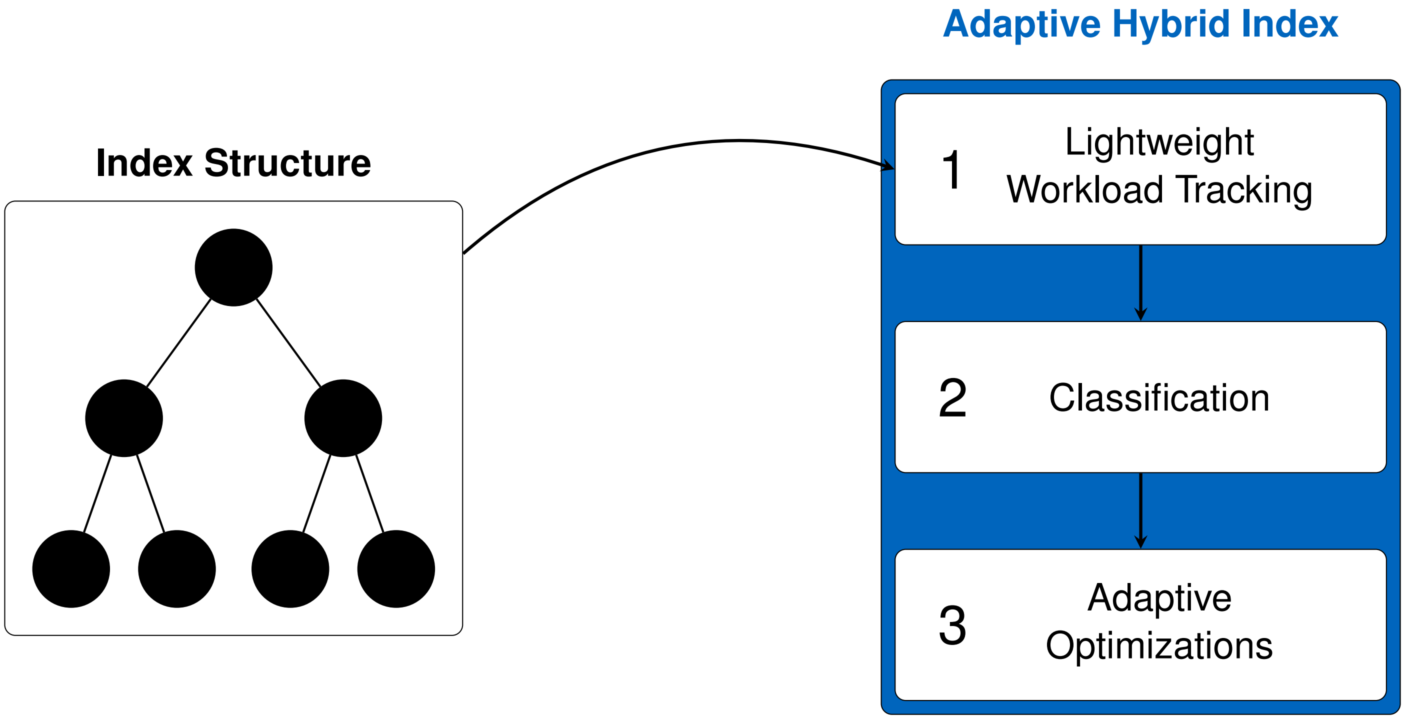
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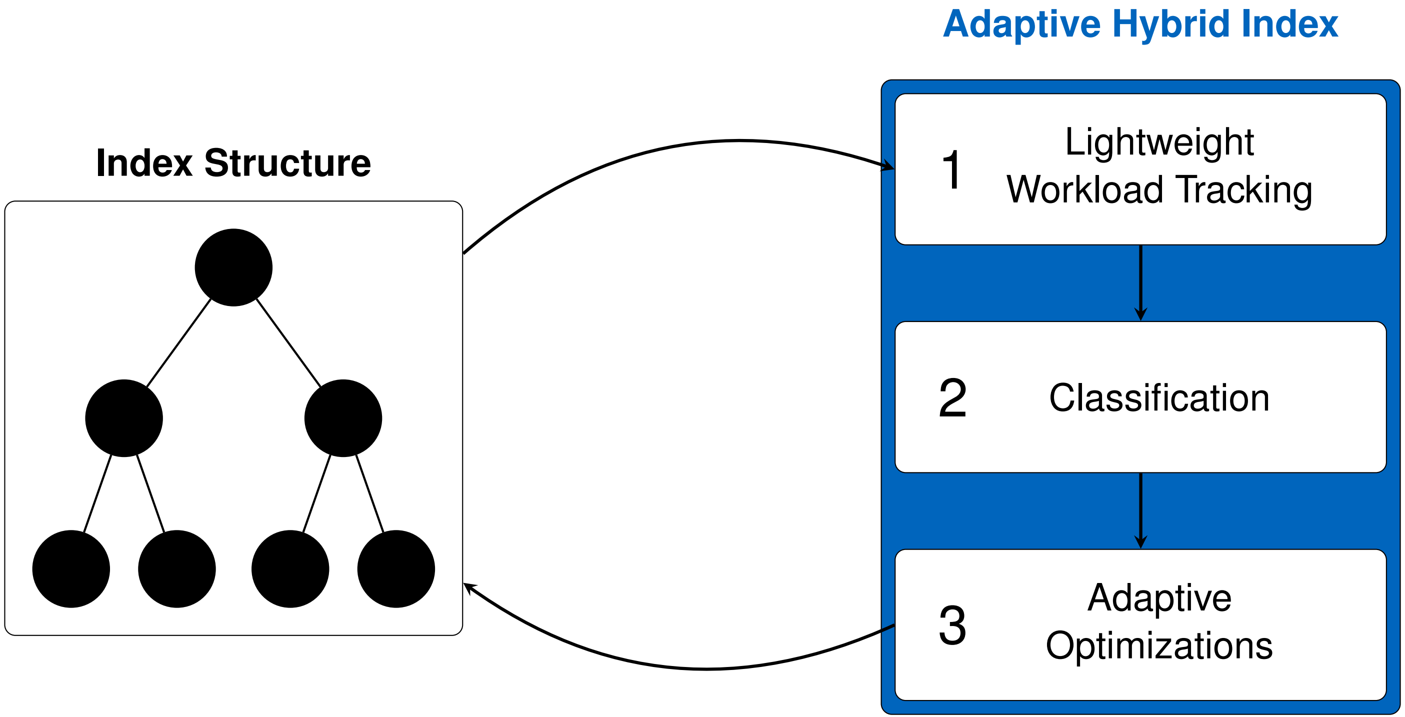
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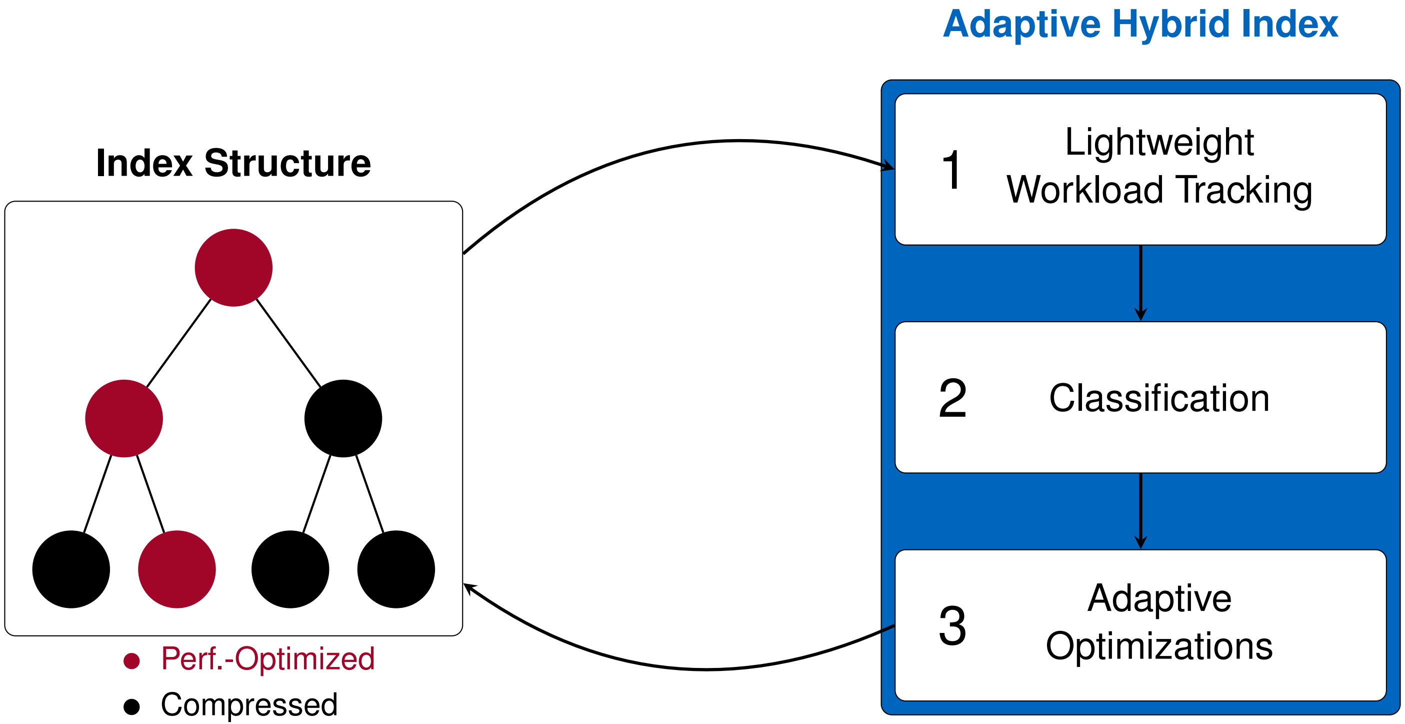
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Perf.-Optimized
Compressed

Sampling Parameters

Frequency

- Low frequencies reduce sampling overhead
- High frequencies allow to promptly react to changing workload

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$\Rightarrow$ **Adaptive Hybrid Indexes choose these parameters adaptively at runtime**

Application I: Adaptive Hybrid B+-Tree

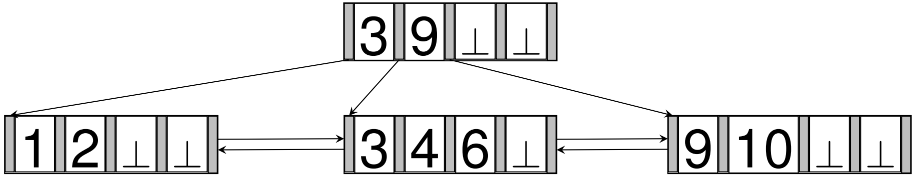

Figure: Example B+-Tree

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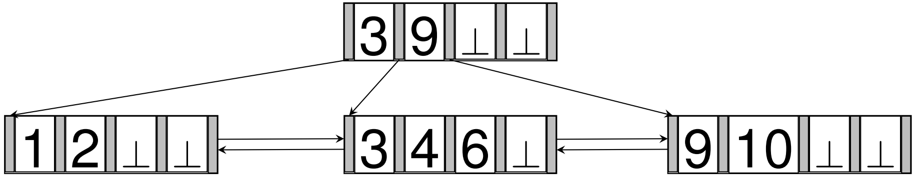

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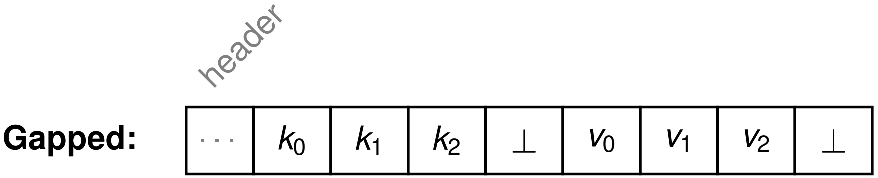

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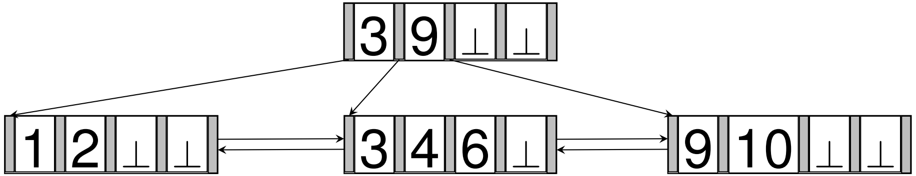

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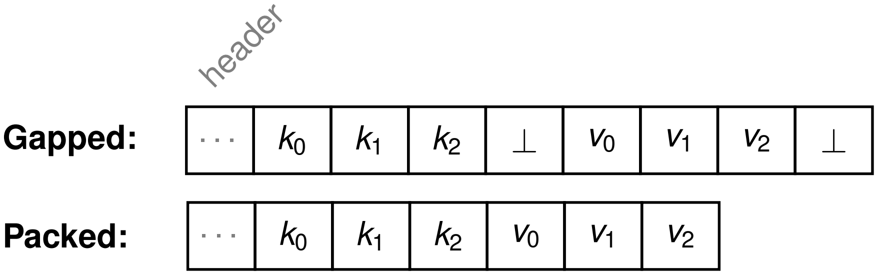

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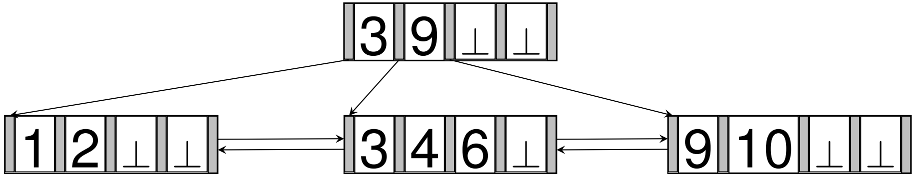

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header

Gapped:

···	k_0	k_1	k_2	$\perp$	v_0	v_1	v_2	$\perp$

Packed:

···	k_0	k_1	k_2	v_0	v_1	v_2

Succinct:

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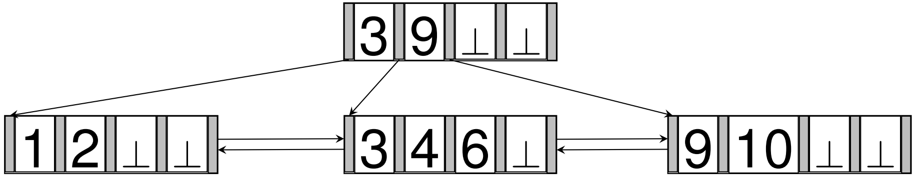

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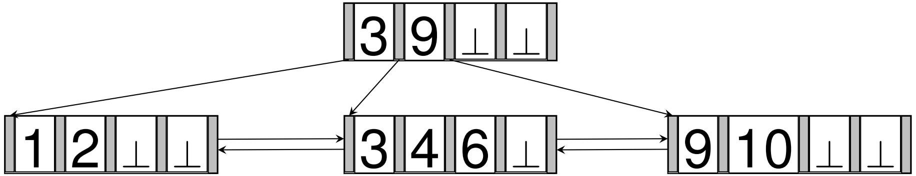

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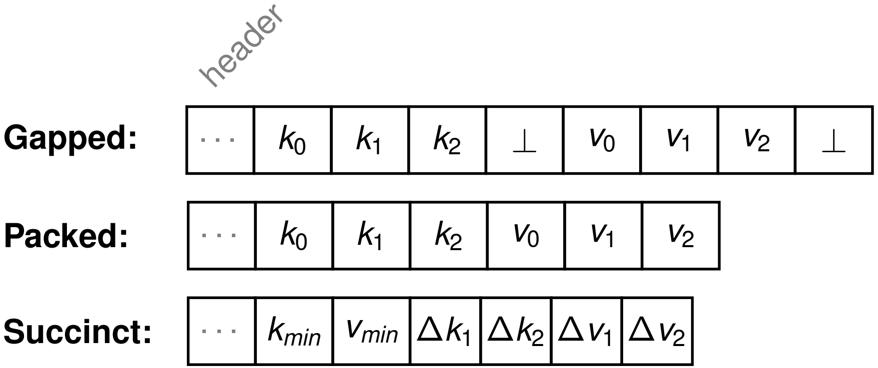

Table: Leaf encodings storing 64-bit key-value pairs and performance implications on lookups.

Leaf Node Encoding	Average Size	Instruc.	LLC Misses	Branch Misses
Gapped	4096B	85	2.1	4.44
Packed	2872B	84	1.4	4.46
Succinct	1076B	341	1.1	6.69

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Application II: Adaptive Hybrid Trie

Level-wise combination of the Adaptive Radix Tree (ART) and the Fast Succinct Trie (FST)

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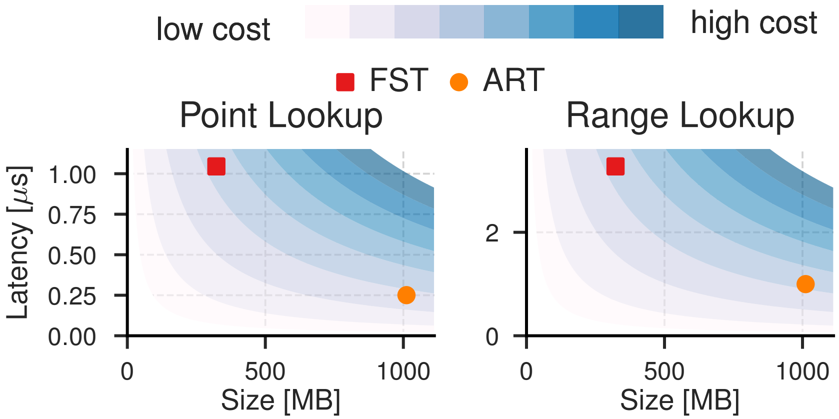

Figure: Query latency and index size of ART and FST

Experiment Setup:

- Dataset: 33M unique email adresses (host-reversed order, e.g. com.foo@<username>)
- Workload: 50% Reads, 50% Scans, key selection follows a Zipf distribution

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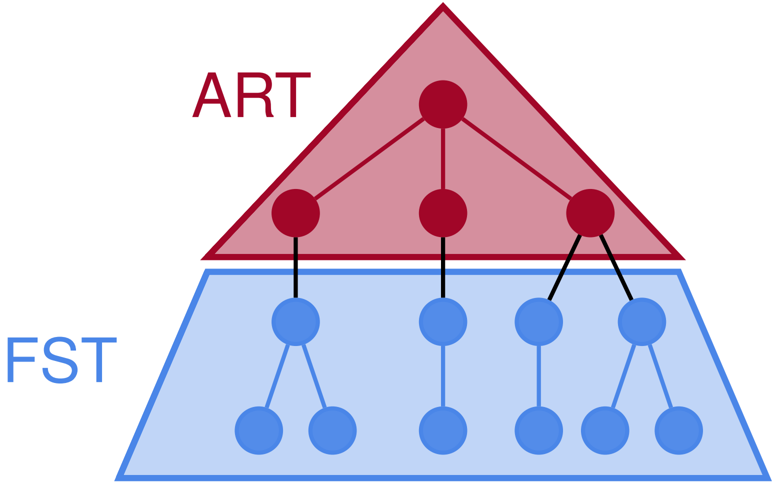

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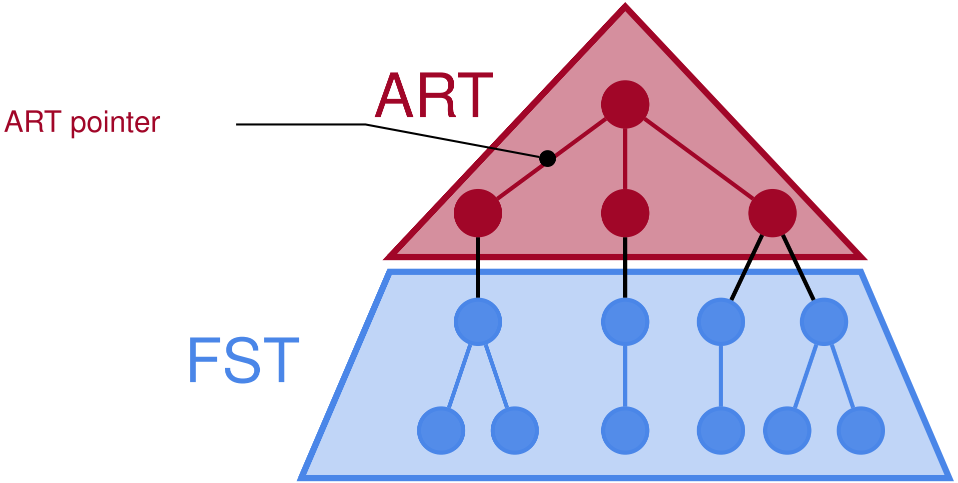

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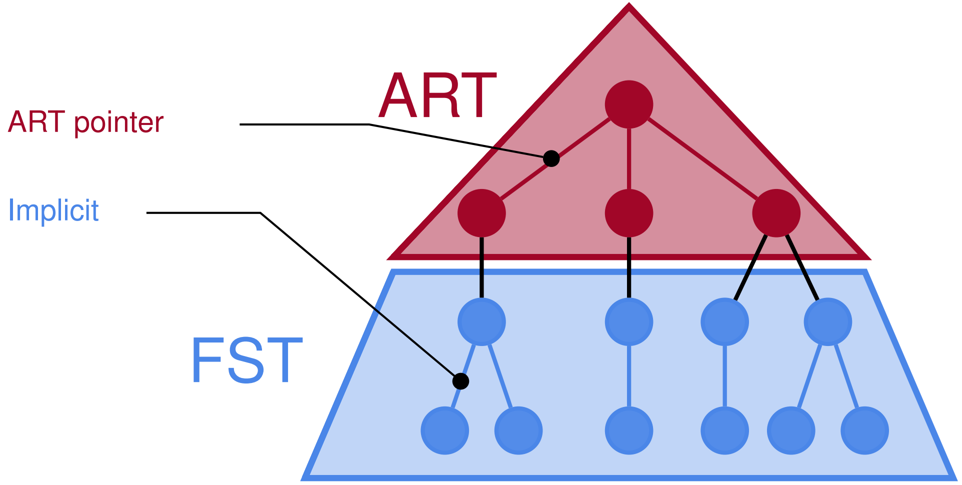

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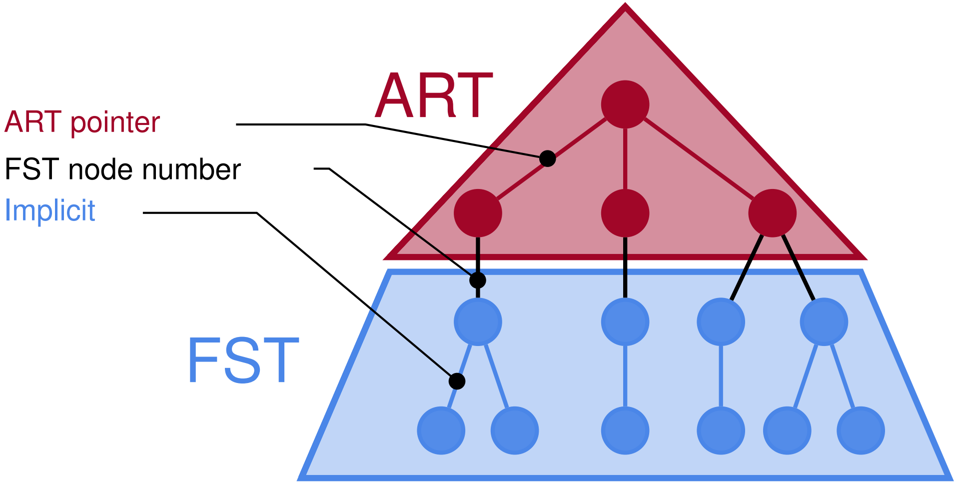

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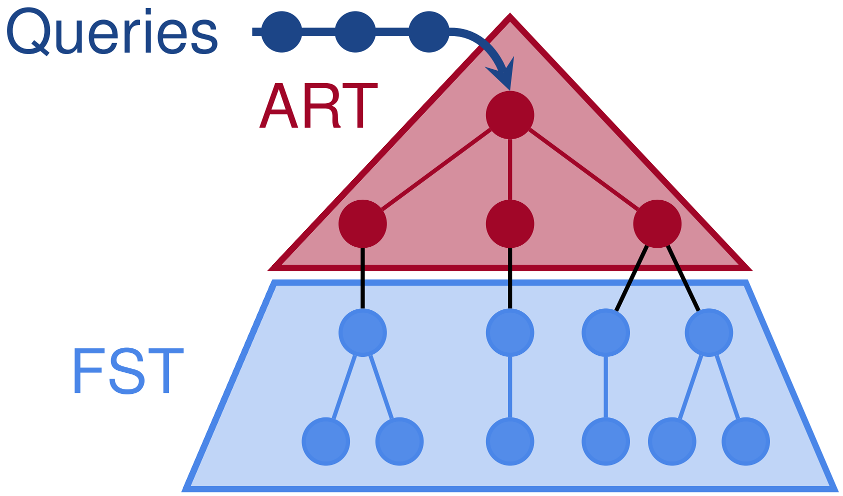

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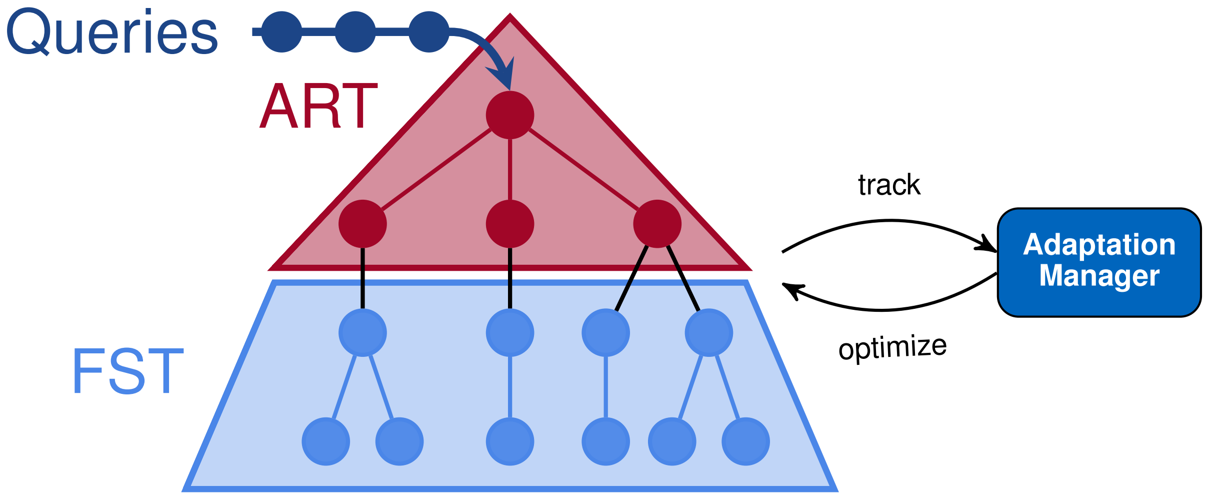

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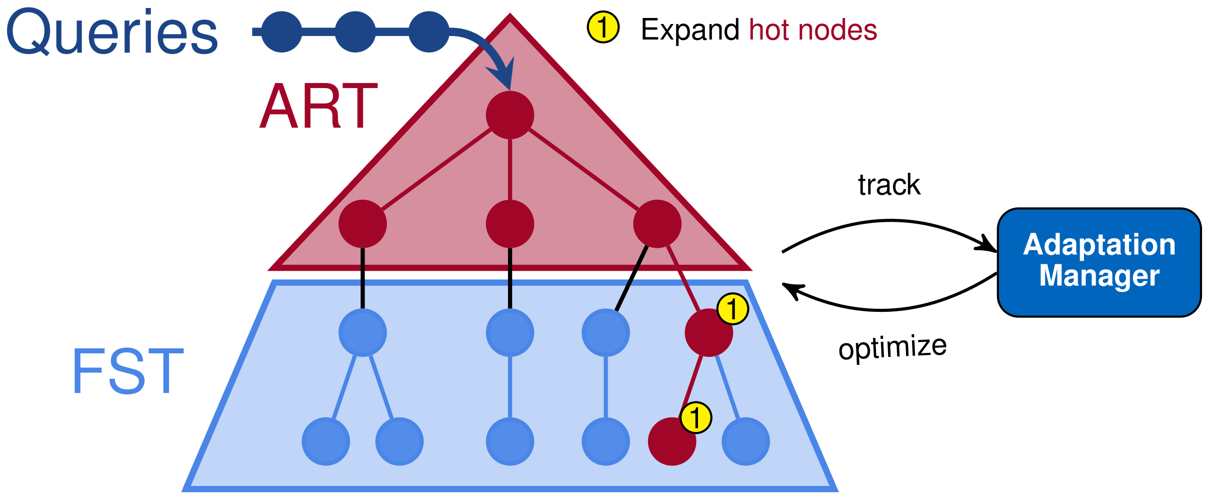

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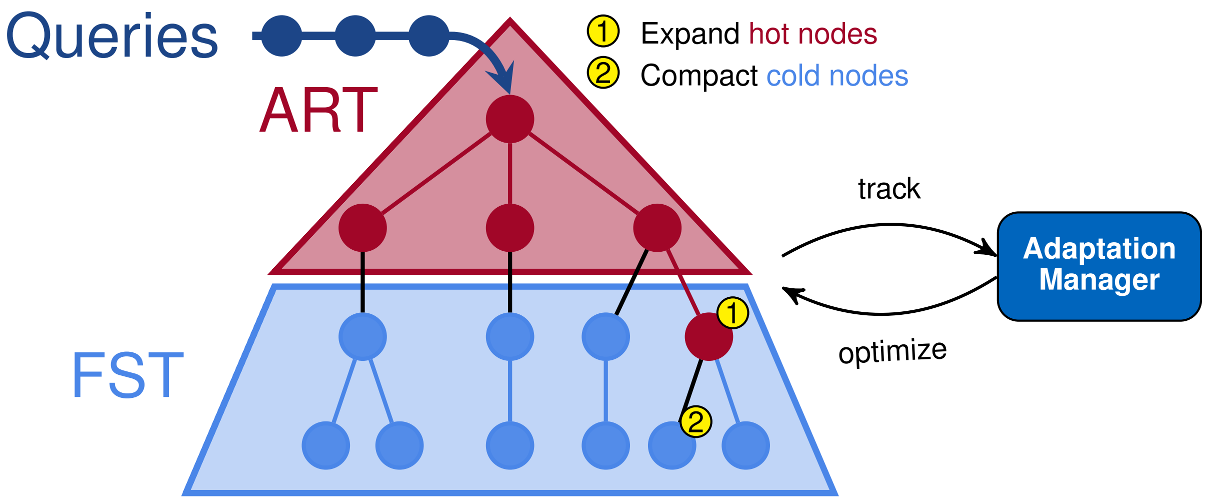
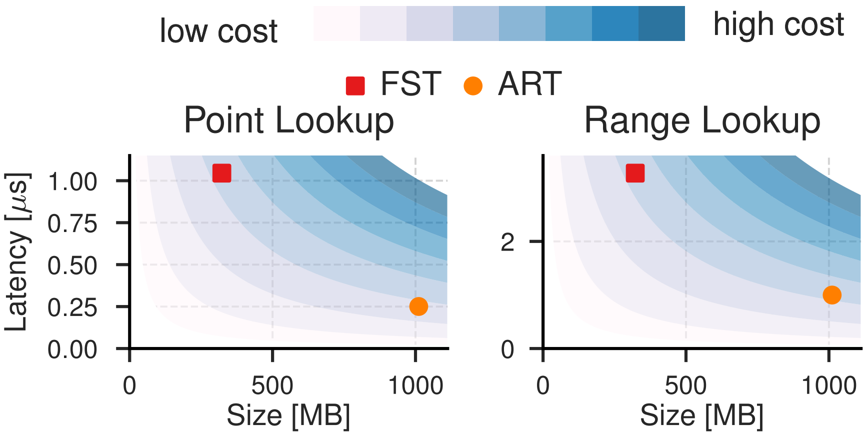


Evaluation

Setup

- 16-core AMD Ryzen 9 3950X CPU @ 3.5GHz
- 64GB DDR4-2667 RAM
- GCC 9.3.0 with flags `O3` and `march=native`
- CPU overhead for sampling, compacting, and expanding nodes is *included* in the plots

Evaluation: Hybrid Trie – Space & Performance



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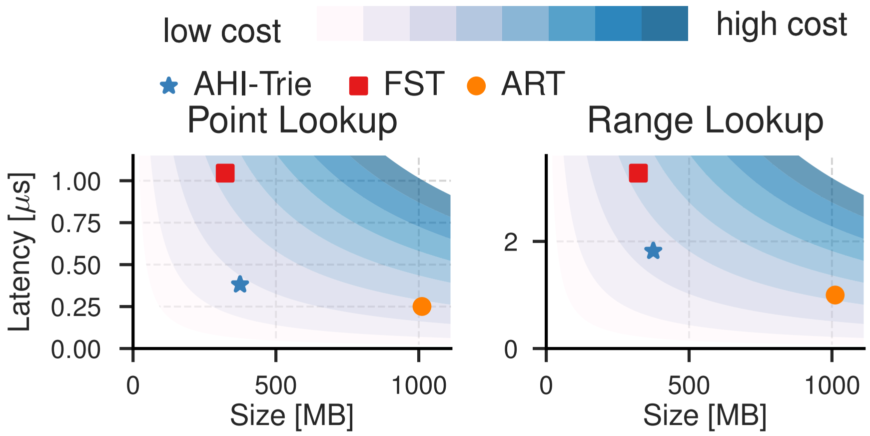

Conclusions:

For point lookups, Hybrid Trie

$\Rightarrow$ reduces index size by 63% comp. to ART

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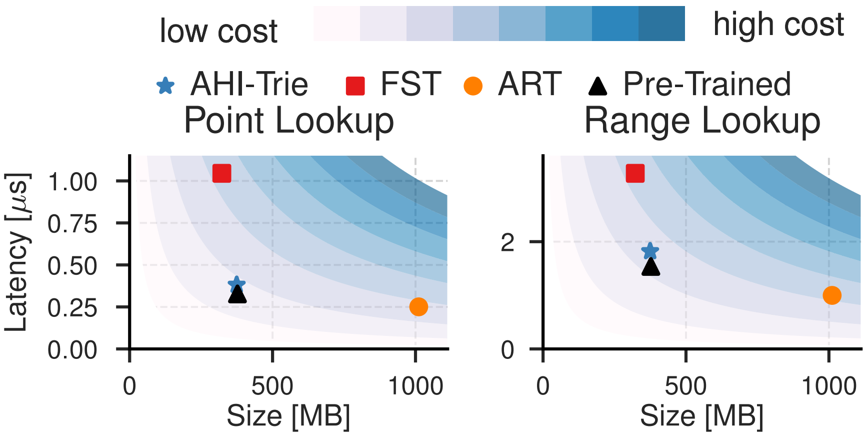

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The Pre-Trained Hybrid Trie does not include tracking-related overhead

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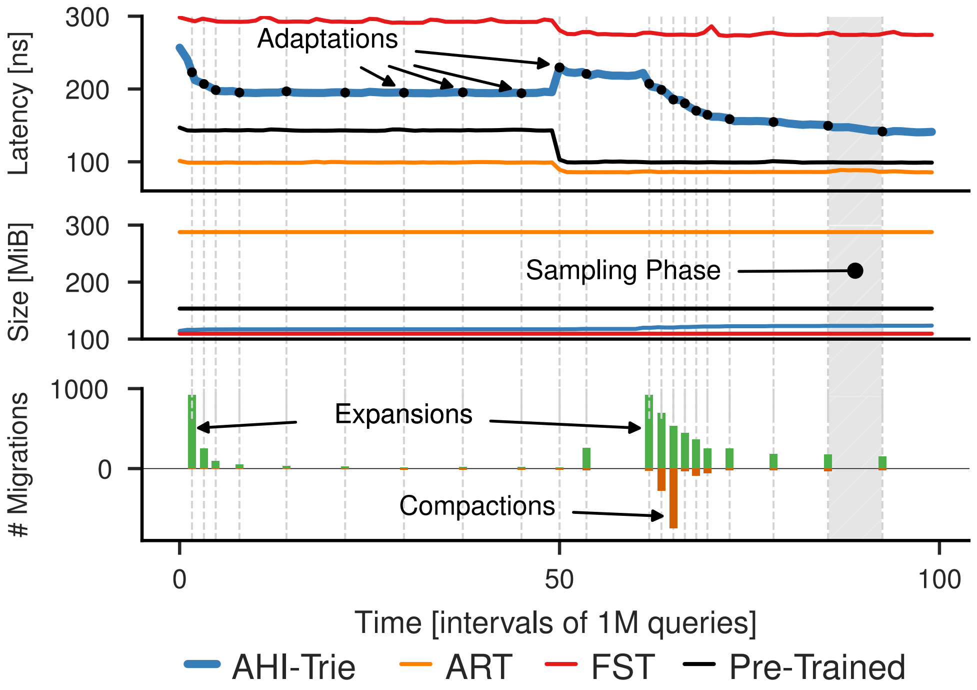

Experiment Setup:

- Dataset: 172M user ids (each 8B)
- Workload: Prefix Random
- Prefix Ranges randomly assigned to two phases

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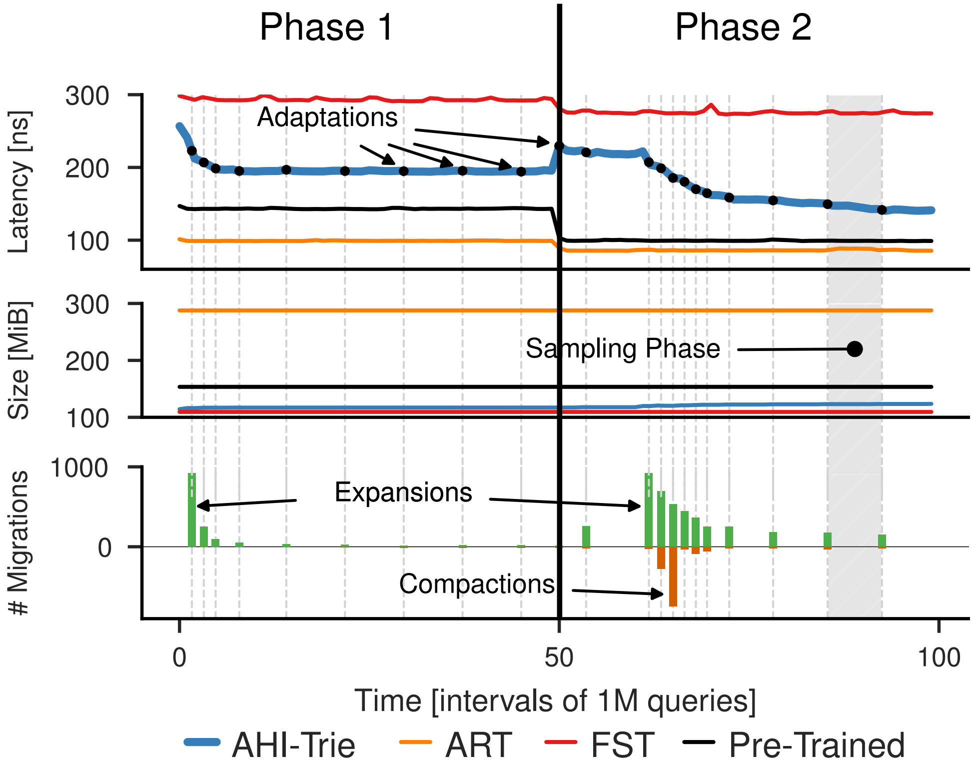

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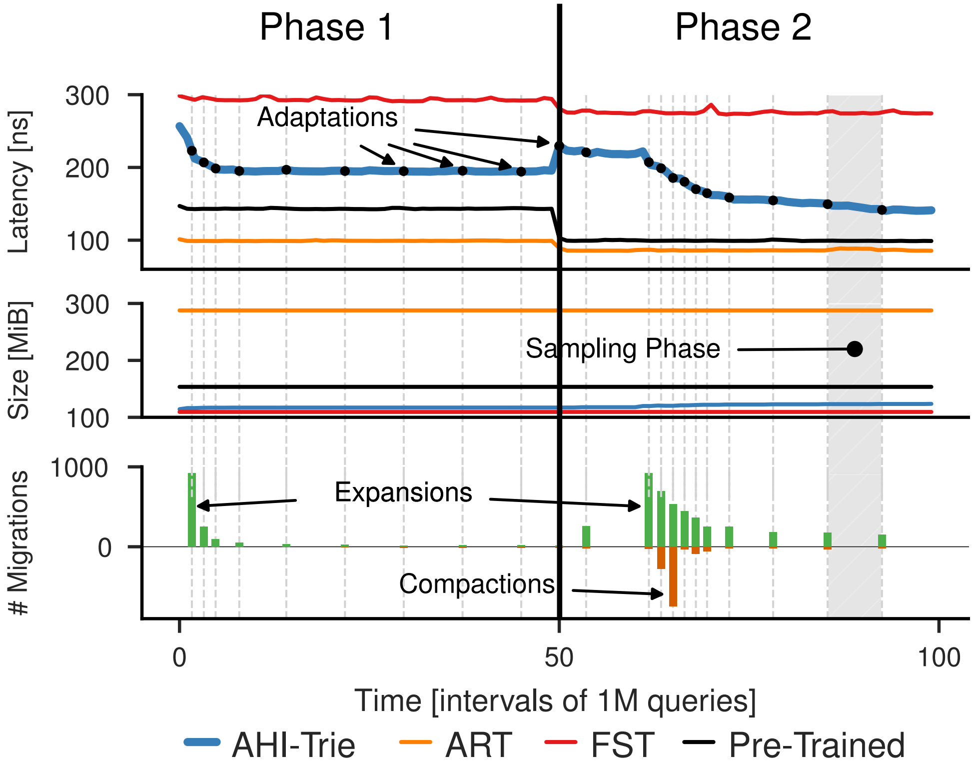

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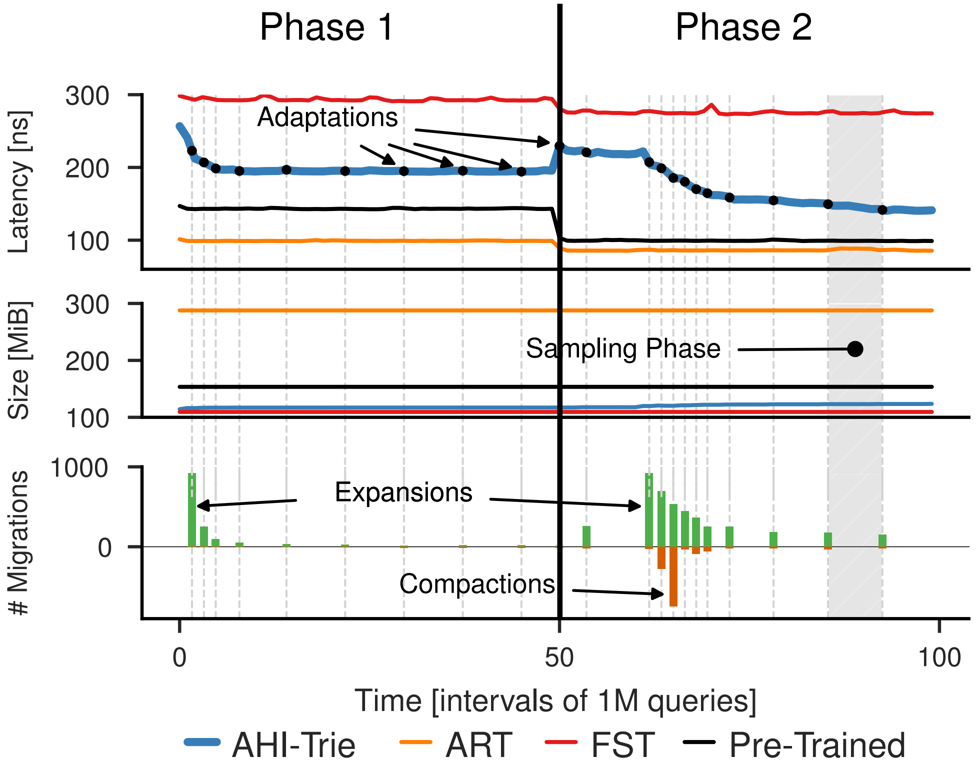

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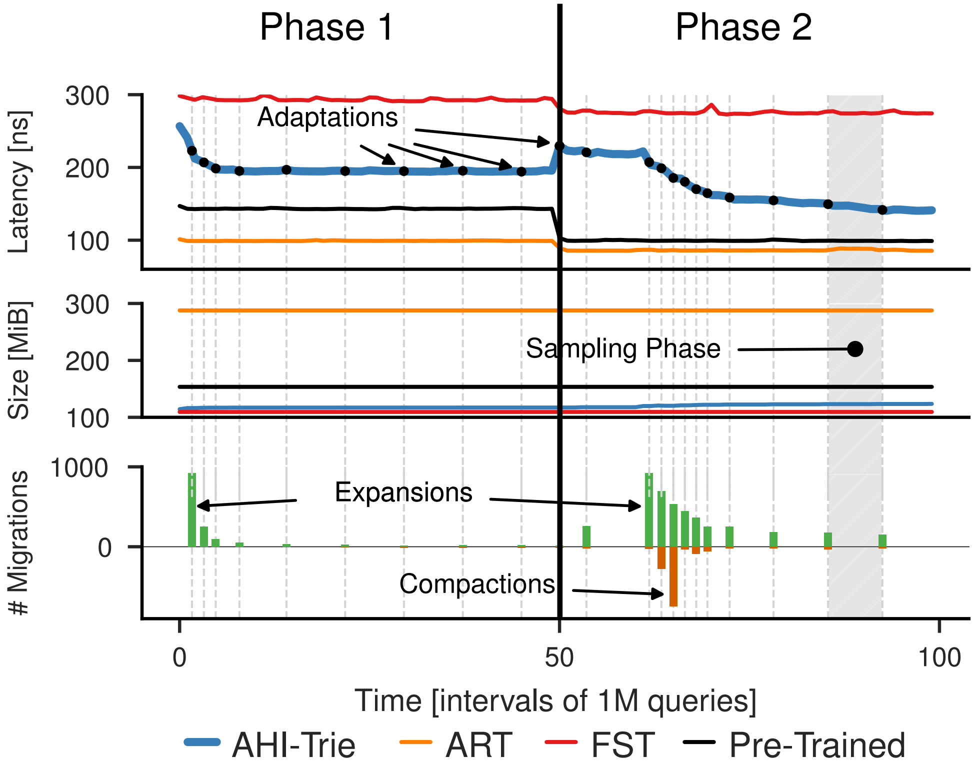

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- ⇒ Sampling frequency changes adaptively with # migrations

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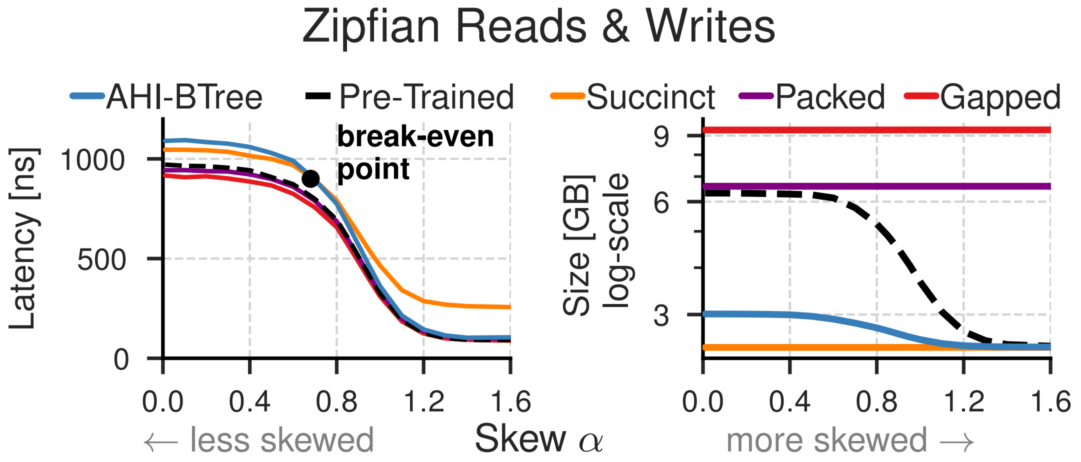
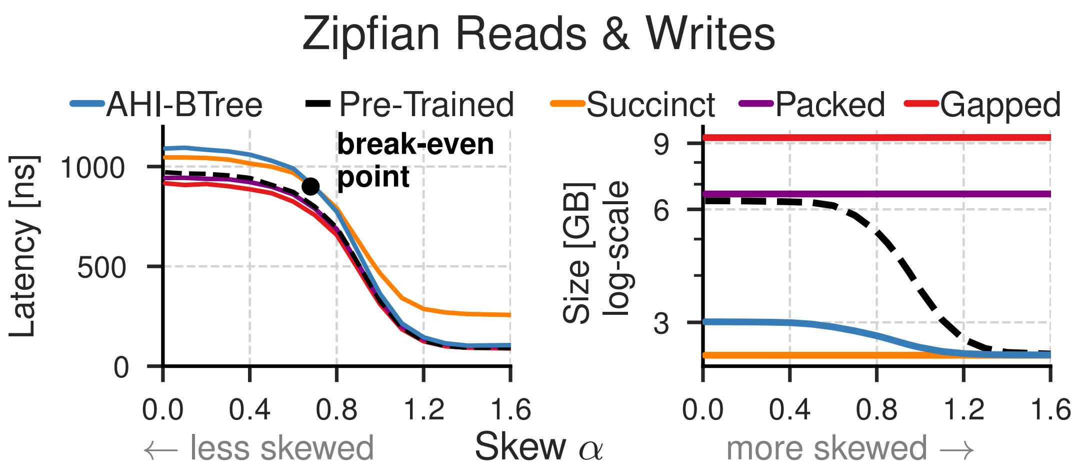


Experiment Setup:

- Dataset: 400M Open Street Map Cell IDs
- Workload: 49% Reads, 49% Scans, 2% Inserts

Evaluation: Hybrid B+-Tree – Skewed Workloads



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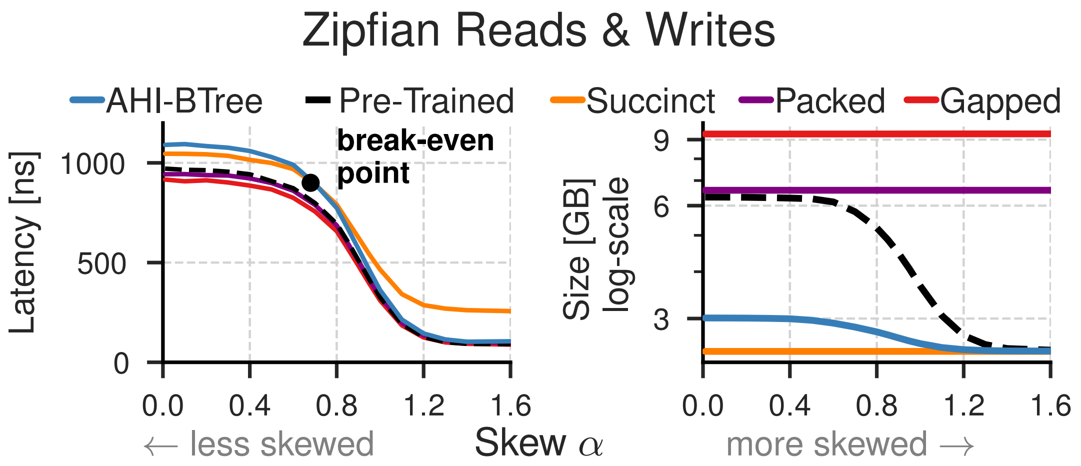

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- Tracking overhead & performance improvements through adaptive optimizations equalize at the break-even point

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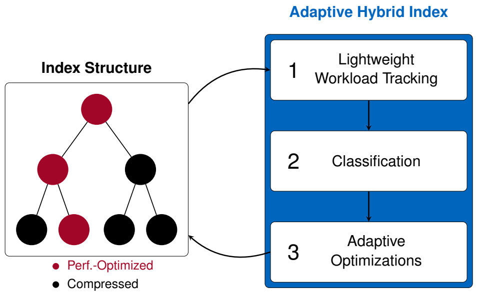

Generic framework to create Adaptive Hybrid Indexes

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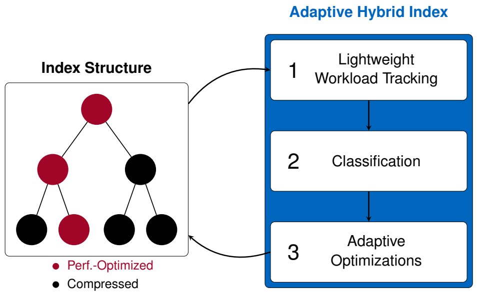

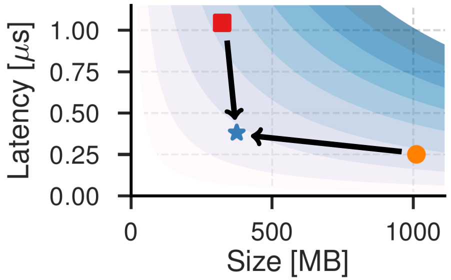

Reduce storage overheads while retaining high performance

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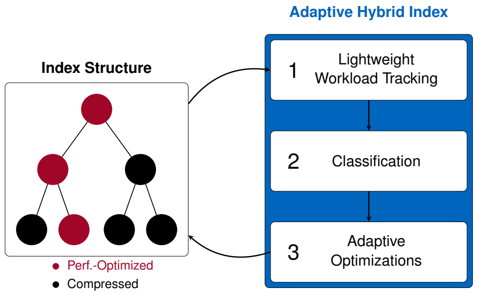

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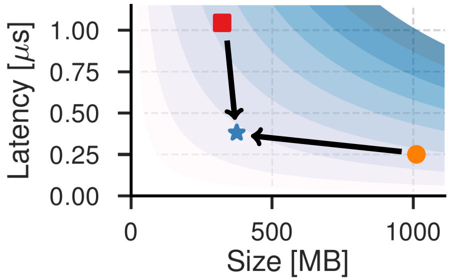

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Evaluated the framework using B+-trees and prefix trees