Adaptive Optimizations for Databases

Christoph Anneser

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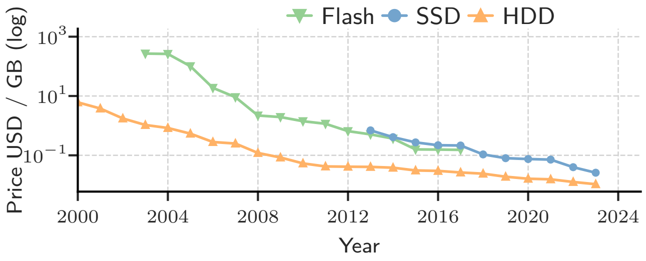
21.05.2024

Introduction



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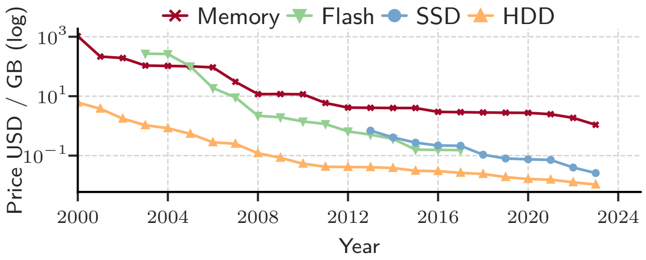
Introduction



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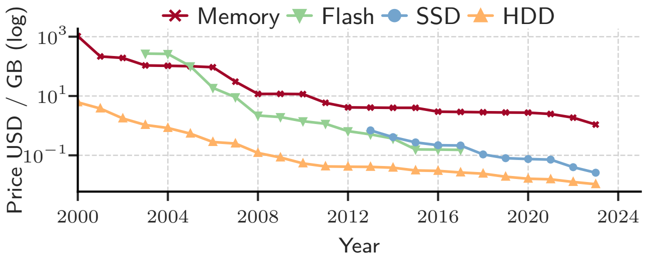

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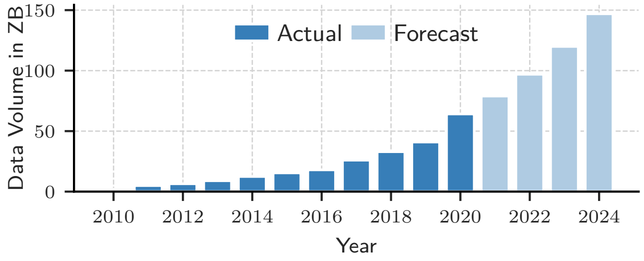

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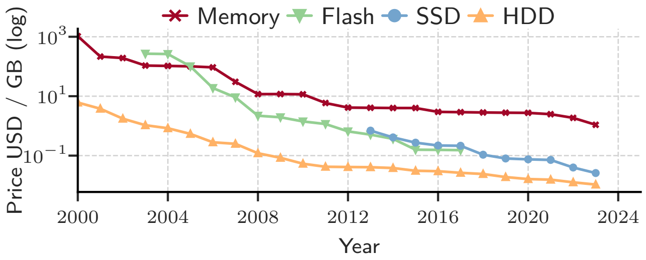

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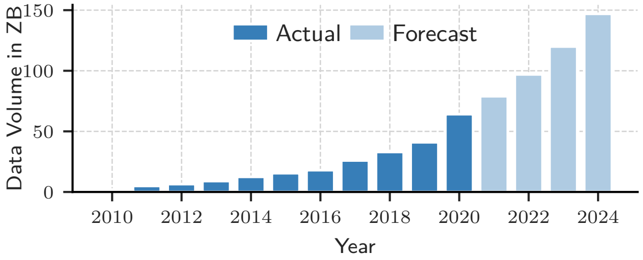

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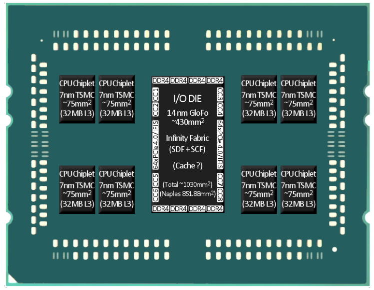
AMD EPYC Rome



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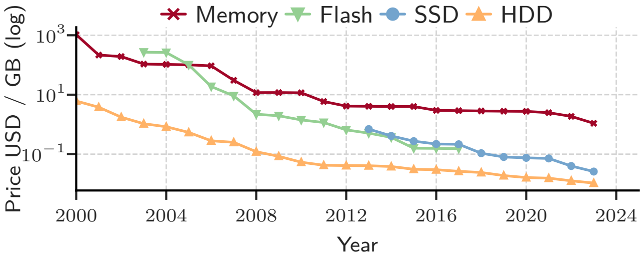

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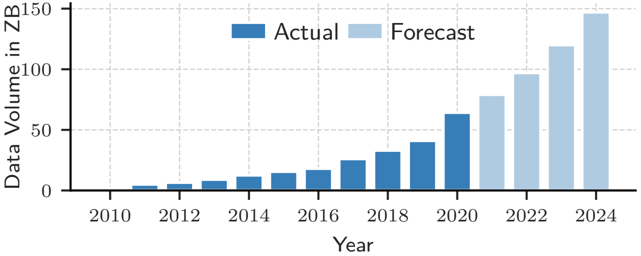

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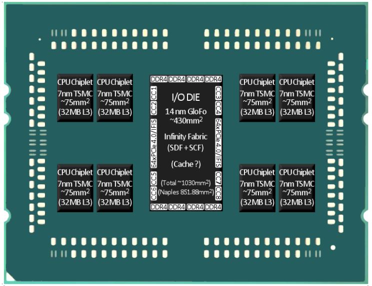

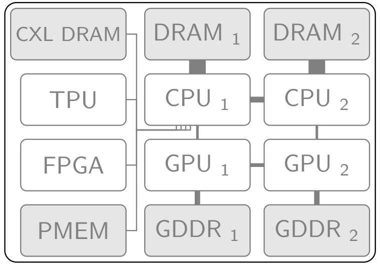

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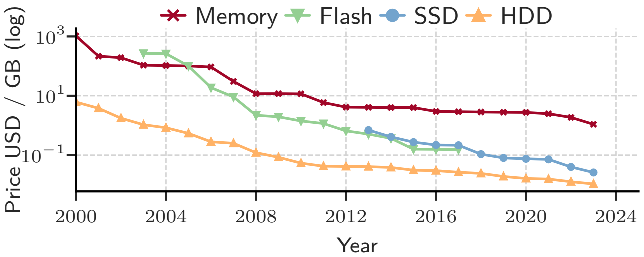

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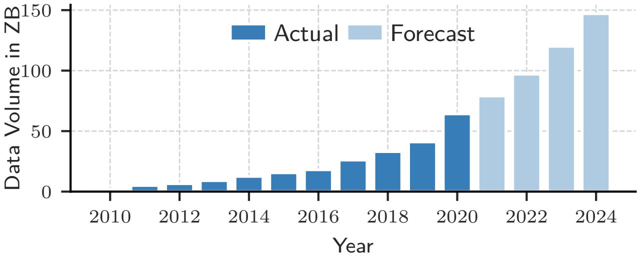

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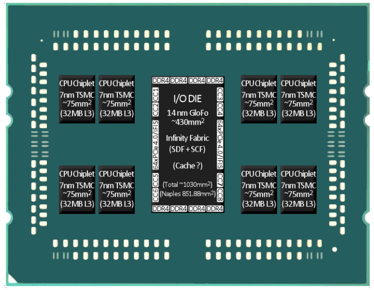

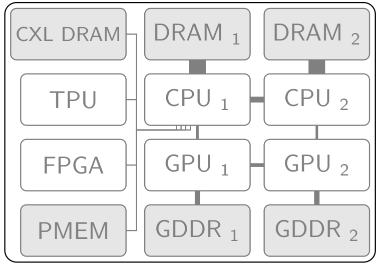

Optimize Data Management Systems for Resource Efficiency Sustainably

Static and Adaptive Optimizations

Static Optimizations

Adaptive Optimizations

Static and Adaptive Optimizations

Static Optimizations

$\Rightarrow$ At development time

$\Rightarrow$ Independent of input data

$\Rightarrow$ Theoretical runtime

Adaptive Optimizations

Static and Adaptive Optimizations

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⇒ At development time

⇒ Independent of input data

⇒ Theoretical runtime

Adaptive Optimizations

⇒ At execution time

⇒ Data distribution & patterns

⇒ Hardware avail. & utilization

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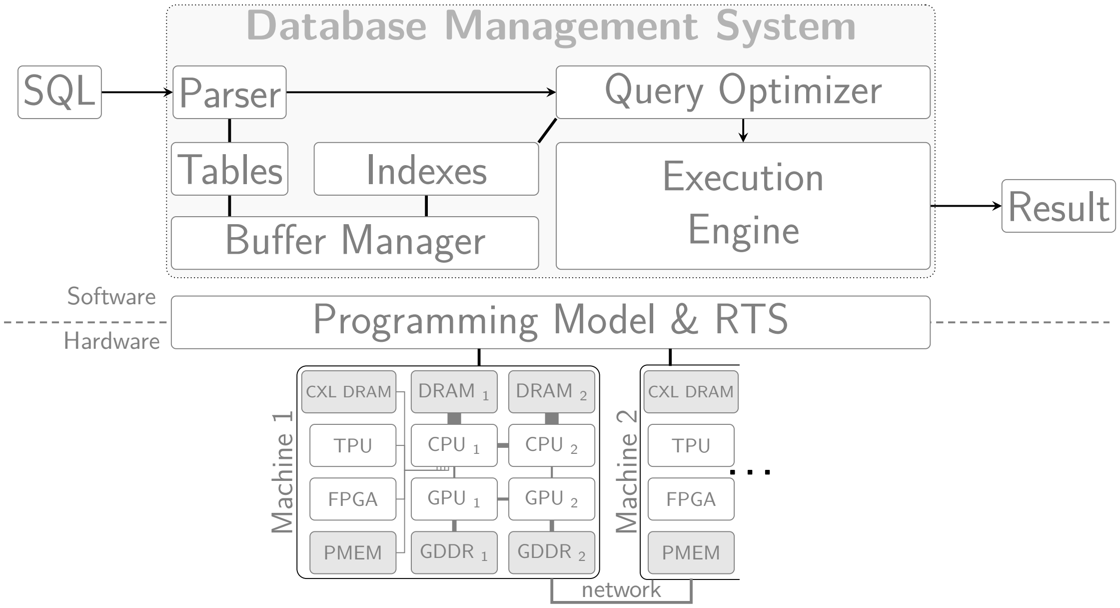
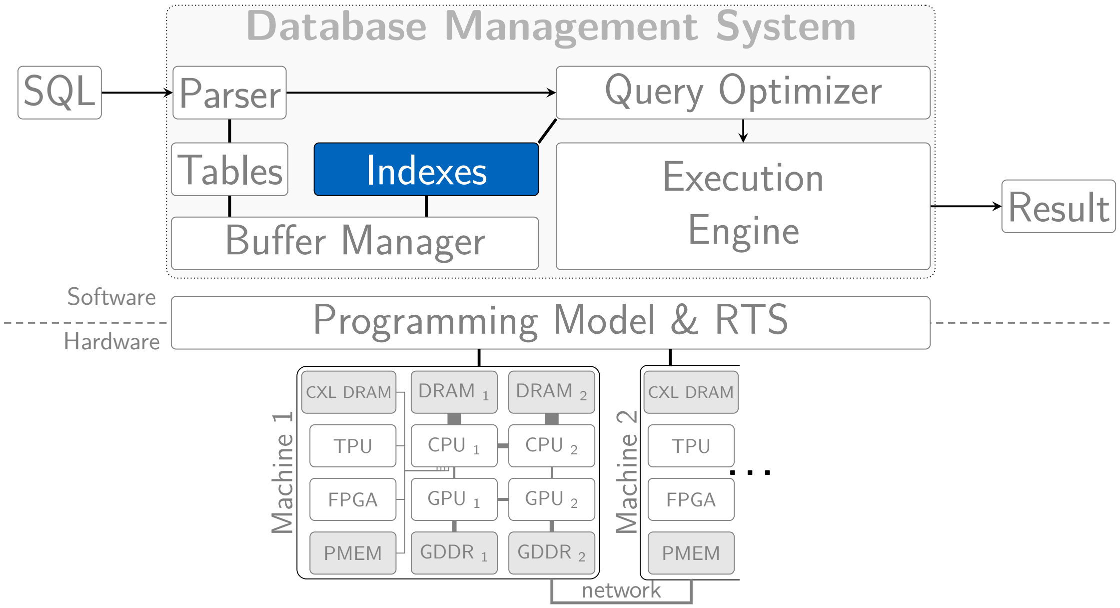
Overview



Database Management System
SQL
Parser
Query Optimizer
Tables
Indexes
Execution Engine
Buffer Manager
Result
Software
Hardware
Programming Model & RTS
Machine 1
CXL DRAM
DRAM 1
DRAM 2
TPU
CPU 1
CPU 2
FPGA
GPU 1
GPU 2
PMEM
GDDR 1
GDDR 2
Machine 2
CXL DRAM
TPU
FPGA
PMEM
...
network

P1: Adaptive Hybrid Indexes



Adaptive Hybrid Indexes

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ABSTRACT

While index structures are crucial components in high-performance query processing systems, they occupy a large fraction of the available memory. Recently-proposed compact indexes reduce this space overhead and thus speed up queries by allowing the database to keep larger working sets in memory. These compact indexes, however, are slower than performance-optimized in-memory indexes because they adopt encodings that trade performance for memory efficiency. Applying different encodings within a single index might allow optimizing both dimensions at the same time – however, it is not clear which encodings should be applied to which index parts at *build-time*.

To take advantage of multiple encodings in *one* index structure, we present a new framework forming the basis of *workload-adaptive hybrid indexes* which moves encoding decisions to *run-time* instead. By sampling incoming queries adaptively, it tracks accesses to index parts and keeps fine-grained statistics which are used for space- and performance-optimized encoding migrations. We evaluated our framework using B+-trees and tries, and examine the adaptation process and space/performance trade-off for real-world and synthetic workloads. For skewed workloads, our framework can reduce the space by up to 82% while retaining more than 90% of the original performance.

CCS CONCEPTS

• **Information systems** → **Data access methods**; **Data layout**.

KEYWORDS

Space-efficient Index; Adaptive Index; Hybrid Index

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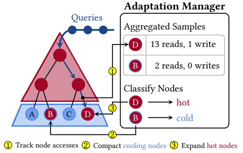


Figure 1: Our sampling-based workload adaptation supports hybrid index structures in choosing the most suitable encoding for each part based on fine-grained access statistics at run-time. It supports user-defined settings such as an upper memory budget and it keeps sampling-related overhead limited by following an adaptive cost-optimized approach.

1 INTRODUCTION

Back in 2006, Jim Gray stated that memory is the new disk and disk is the new tape [5]. This also applies to modern database systems that store the entire data in random access memory (RAM) to allow real-time analyses for trading companies and financial services, for example. They need to process large datasets efficiently to react to new developments and updates within a few milliseconds.

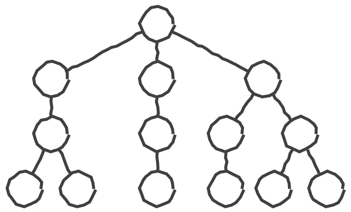
While the DRAM-prices have been stable during the last six to seven years, the data collected by sensors, smartphones, social media platforms, IoT-devices, and digital market-places *increases at a high rate* resulting in data overflows [54], and storing all data in memory becomes infeasible in many cases. However, as in-memory database systems become more and more popular for performance-critical businesses, AWS offers RAM instances that are optimized for in-memory database systems [1]. These instances are equipped with in-memory capacities of up to 24 TB, but the hourly cost of such an instance is more than $120.

To achieve high-performance query-processing for real-time analyses, index structures such as B-trees, tries, and hash tables are widely used by DBMSs. Because there might be multiple indexes per table, especially in OLTP DBMSs, the storage overhead for indexes can be significant. In many cases, more than half of the available memory of a DBMS can be attributed to index structures [54].

@SIGMOD'22

Adaptive Hybrid Indexes – Problem

- **Index structures** are essential for fast query processing



Adaptive Hybrid Indexes – Problem

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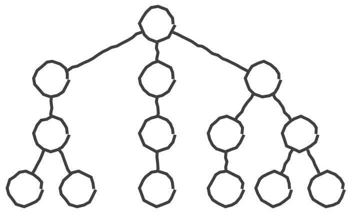

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- **Index structures** are essential for fast query processing
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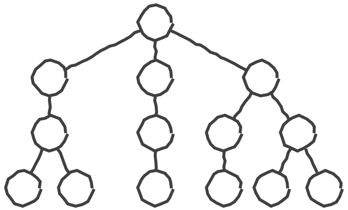
  - Make up to 50% of the memory footprint of a DBMS



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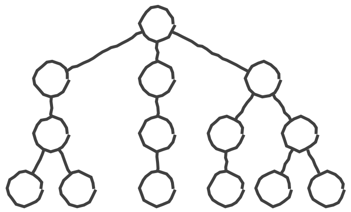
  - Compression almost always incurs some overhead!



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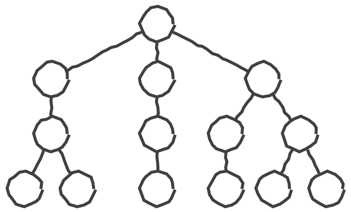

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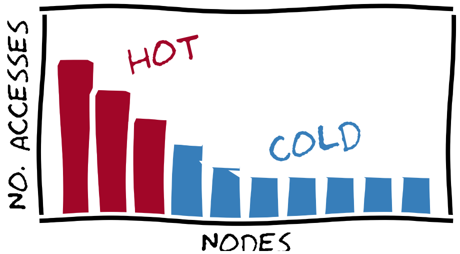

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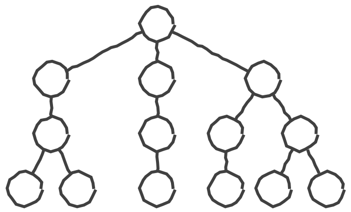
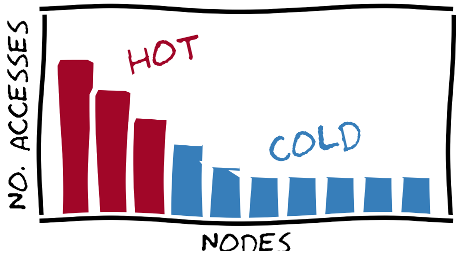


- Real-world workloads are **skewed**
  - Information is available at run-time and depends on the workload



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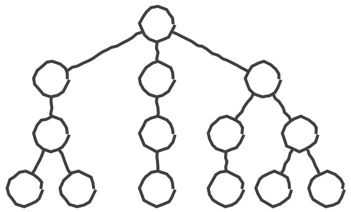
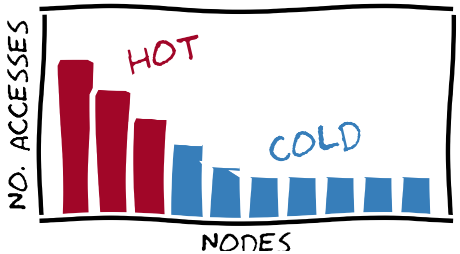


Optimize at run-time



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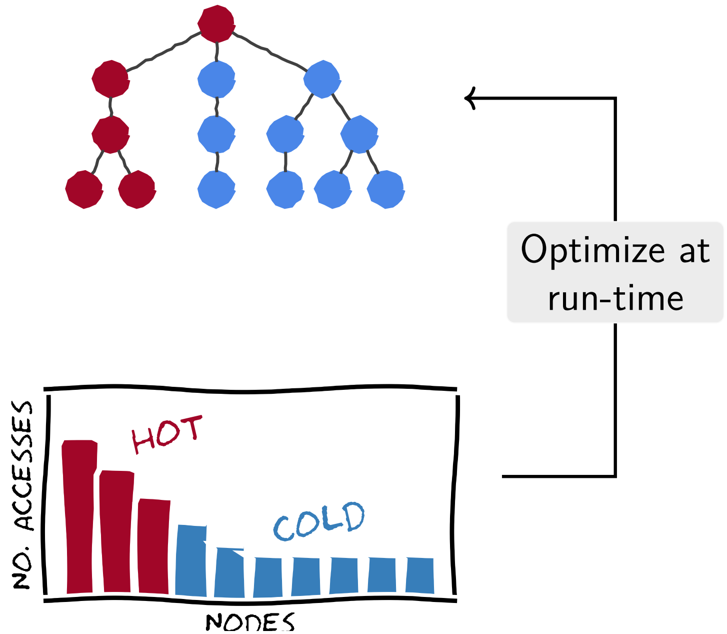
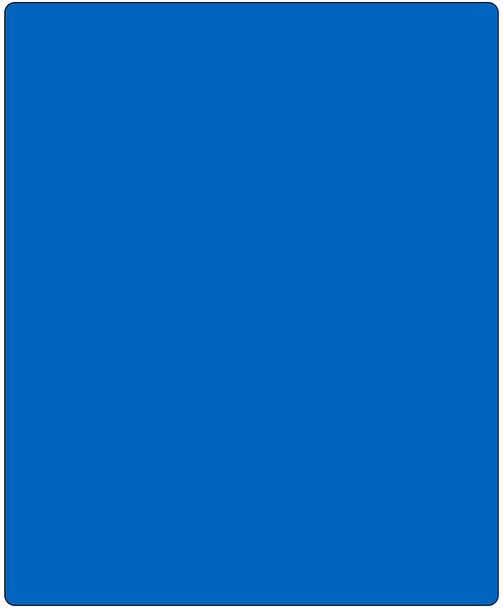
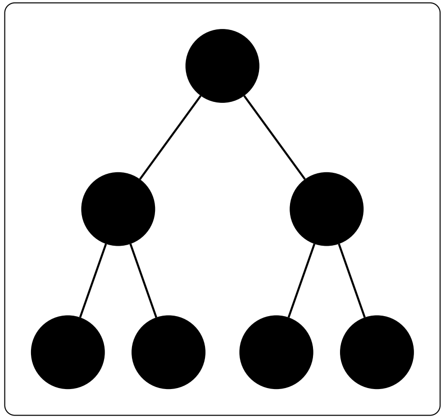


Adaptive Hybrid Indexes – Solution

Adaptive Hybrid Index



Index Structure



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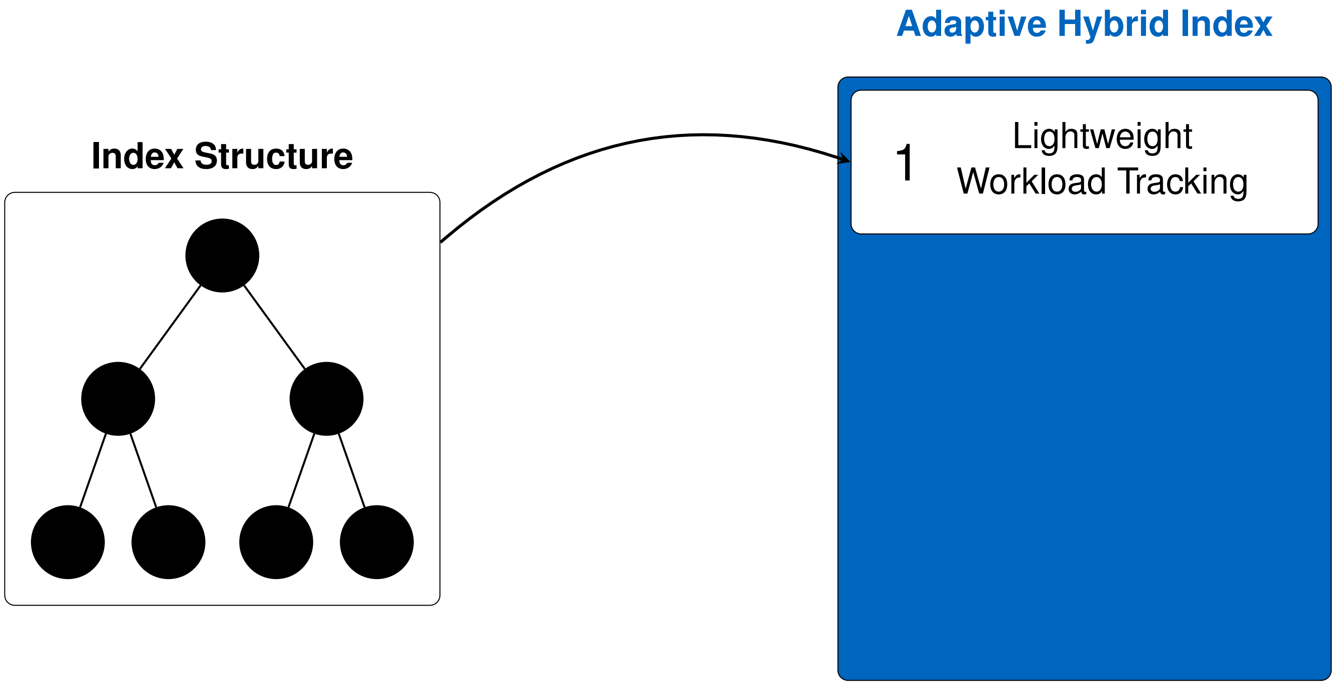

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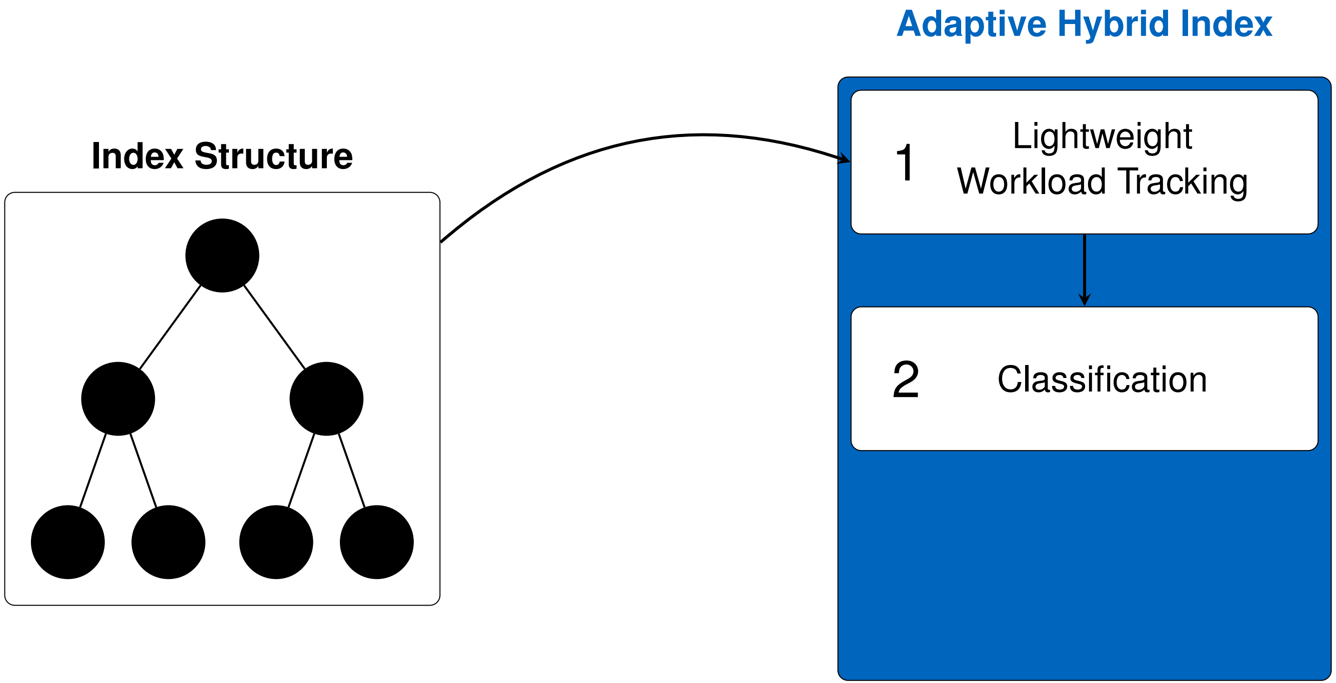

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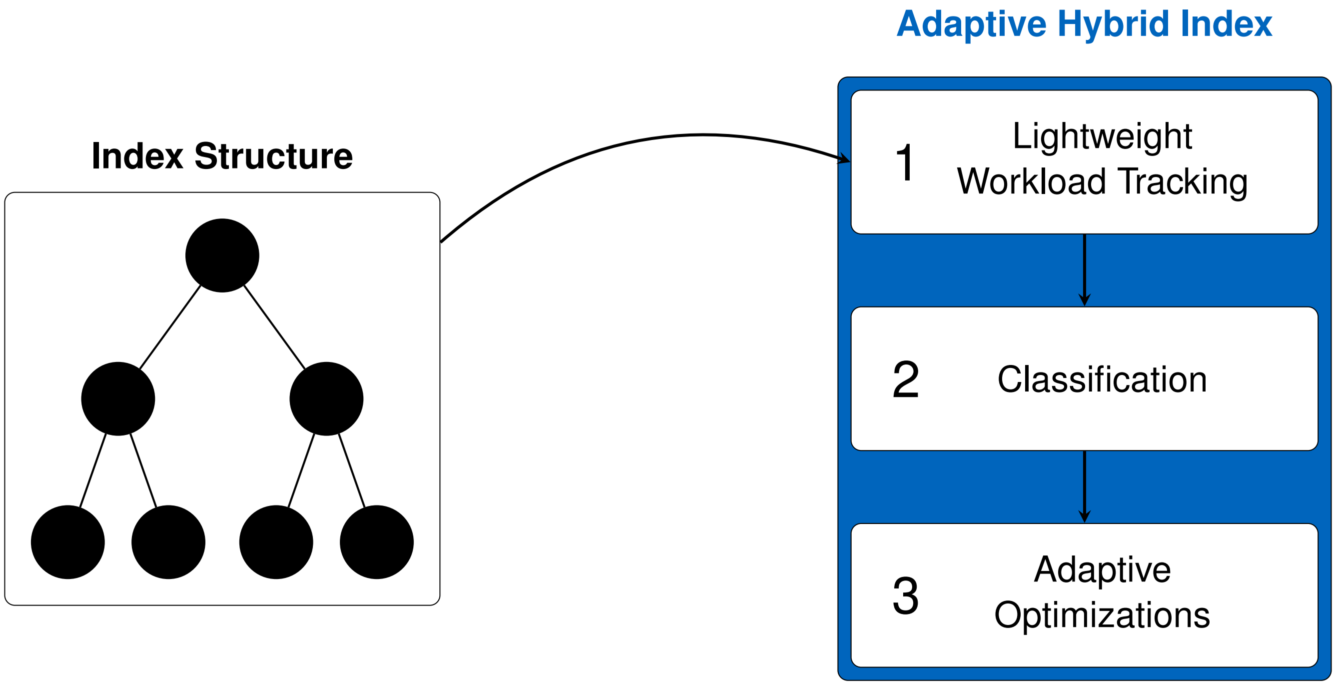

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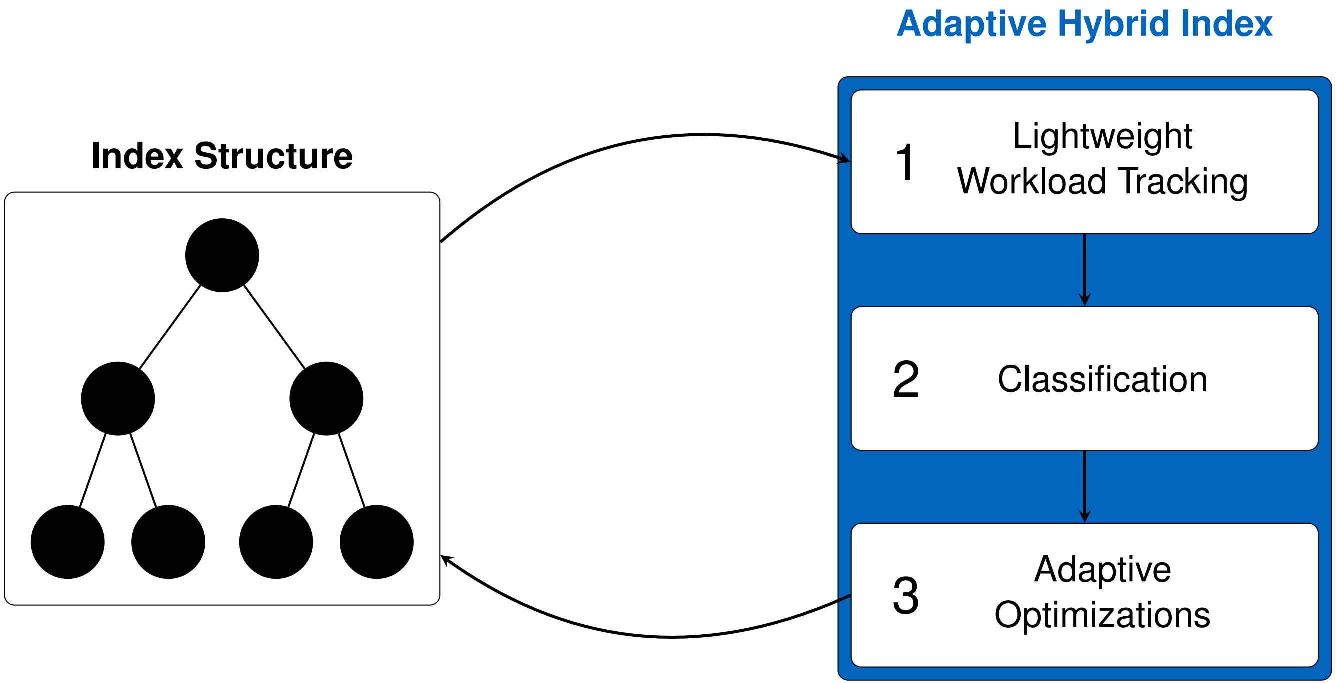

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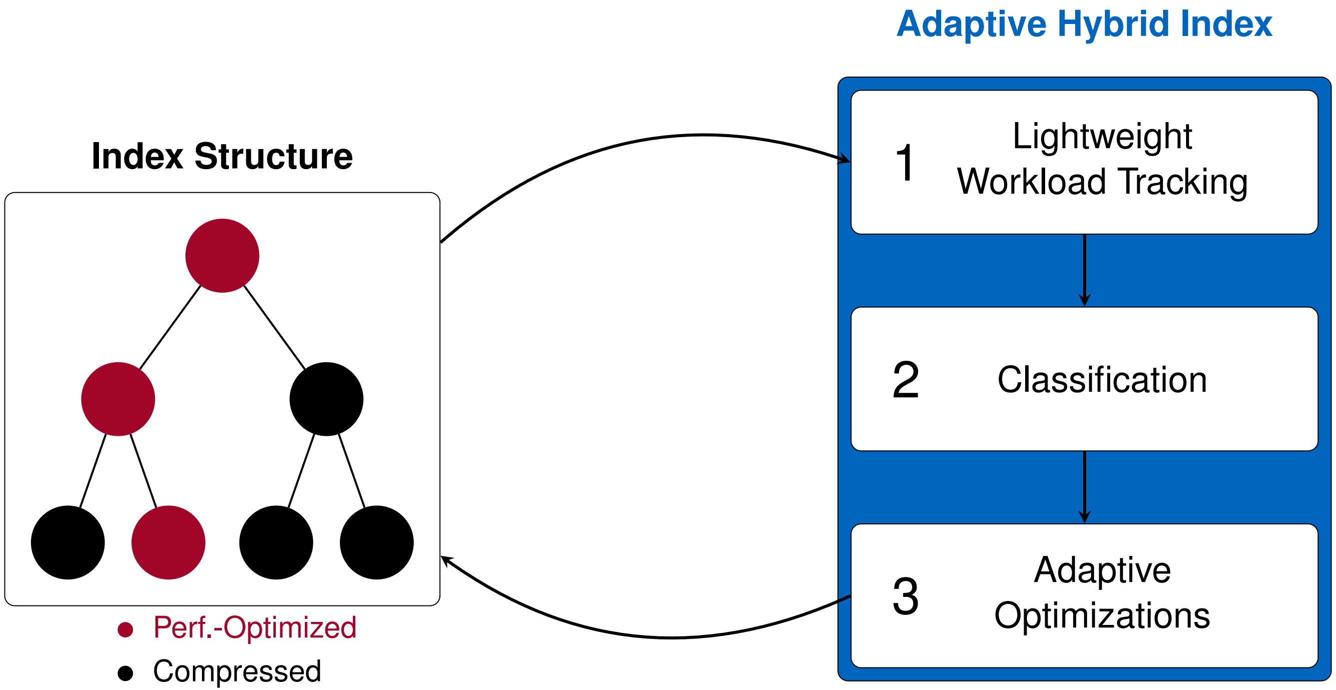

Adaptive Hybrid Trie

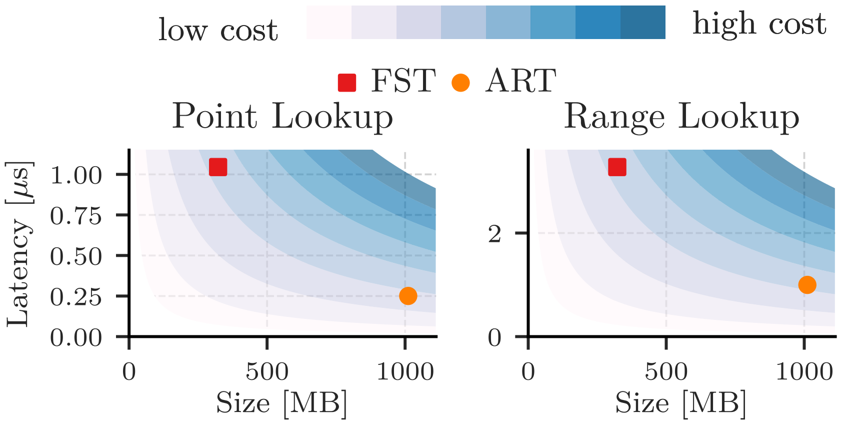

Figure: Query latency and index size of ART and FST

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
- Setup: 16-core AMD Ryzen 9 3950X CPU @ 3.5GHz, 64GB DDR4 RAM
- Compiler: GCC 9.3.0 with flags `O3` and `march=native`

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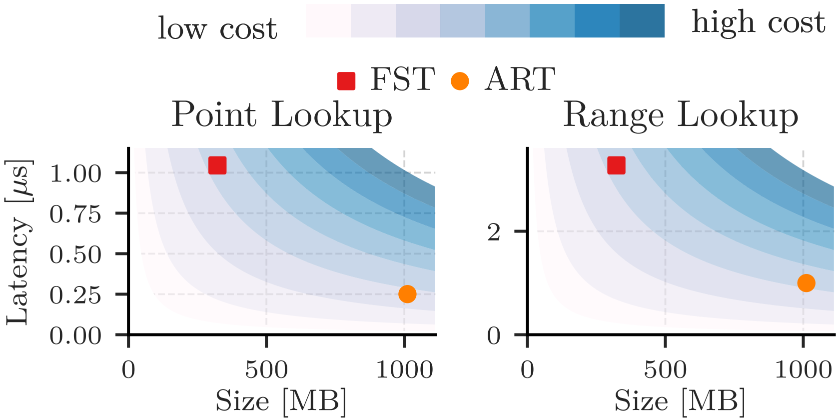

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Adaptive Hybrid Trie is a level-wise combination of ART and FST!

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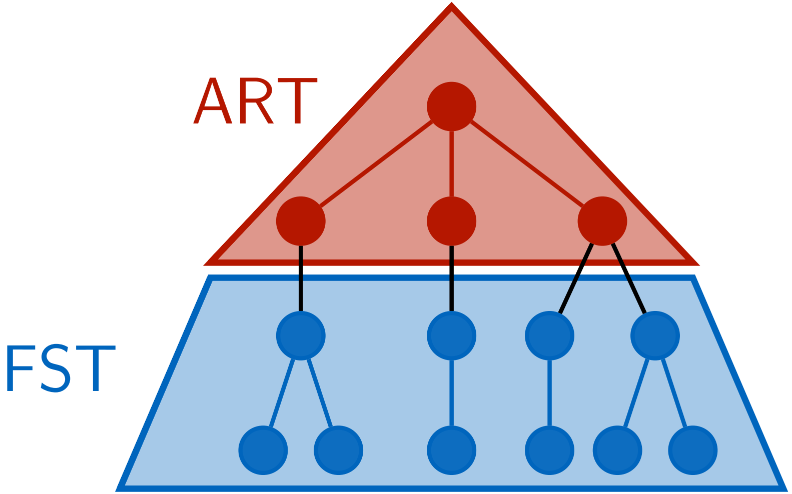

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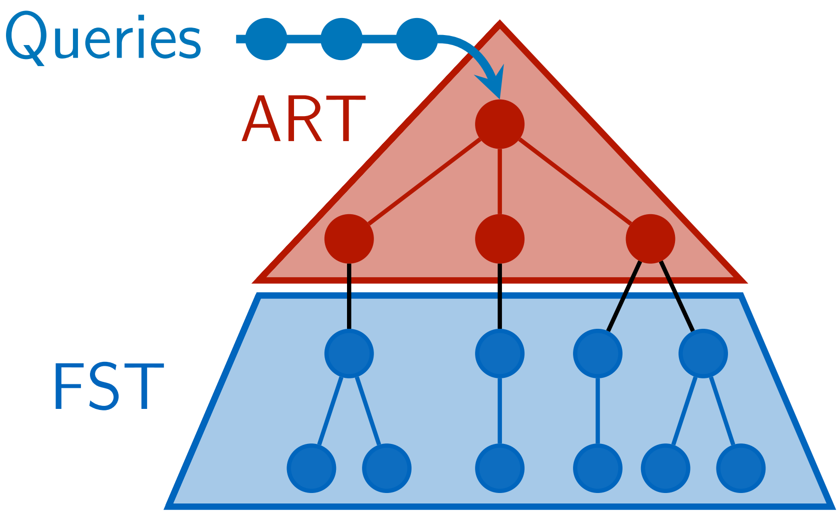

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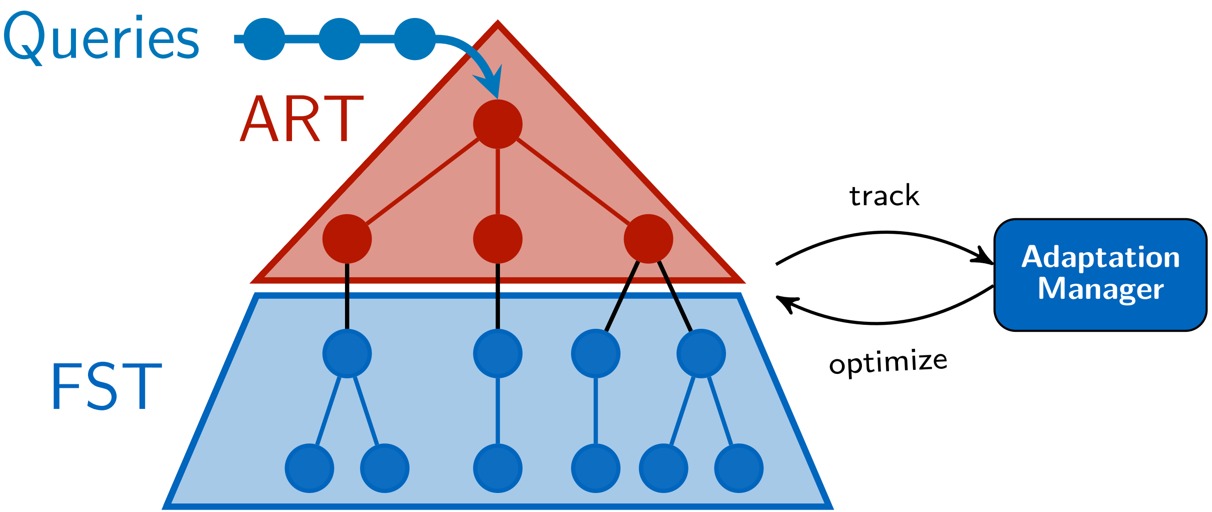

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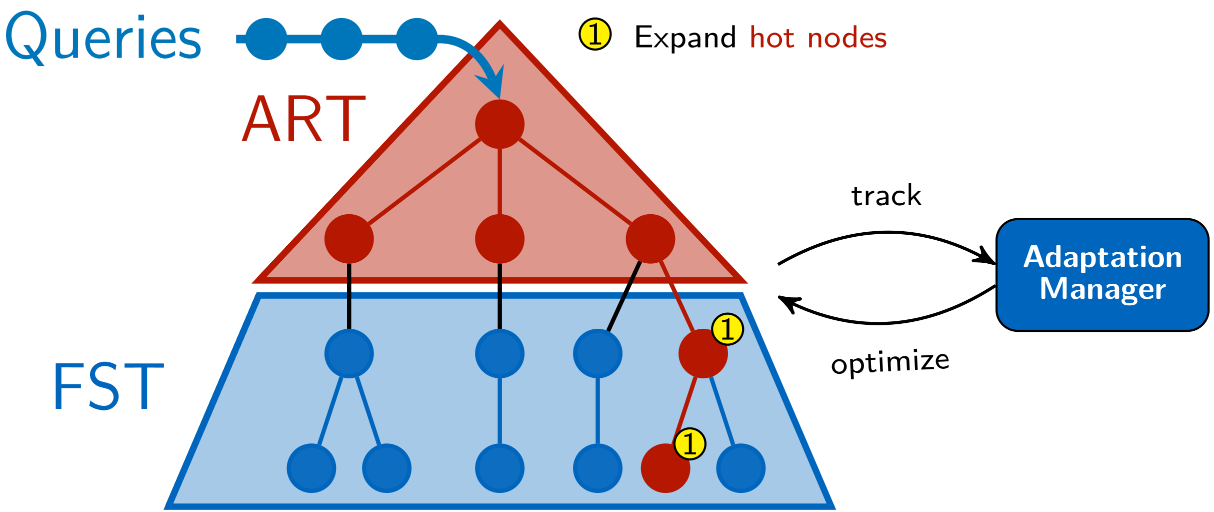

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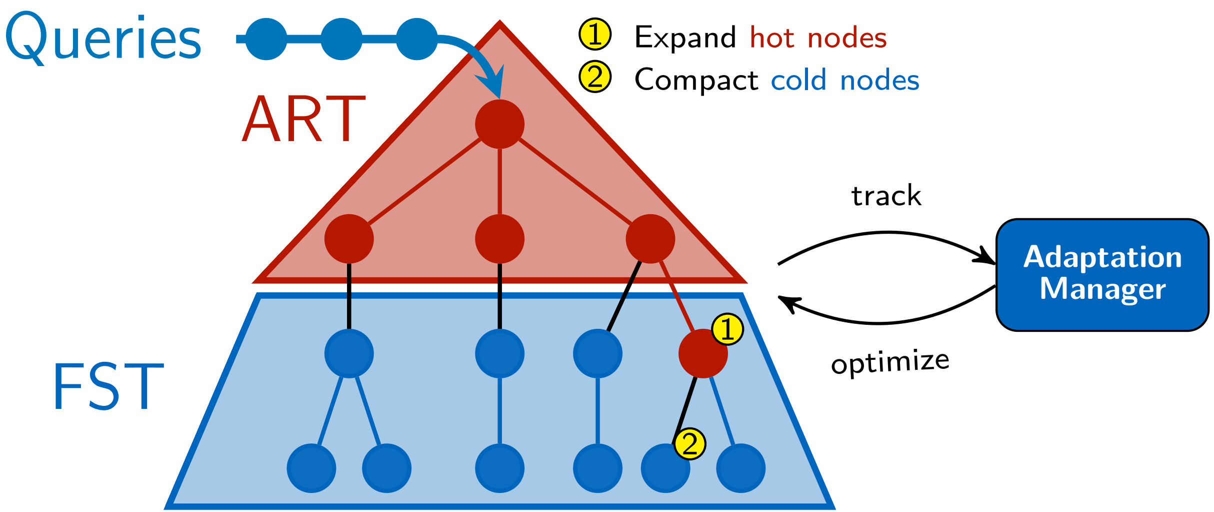
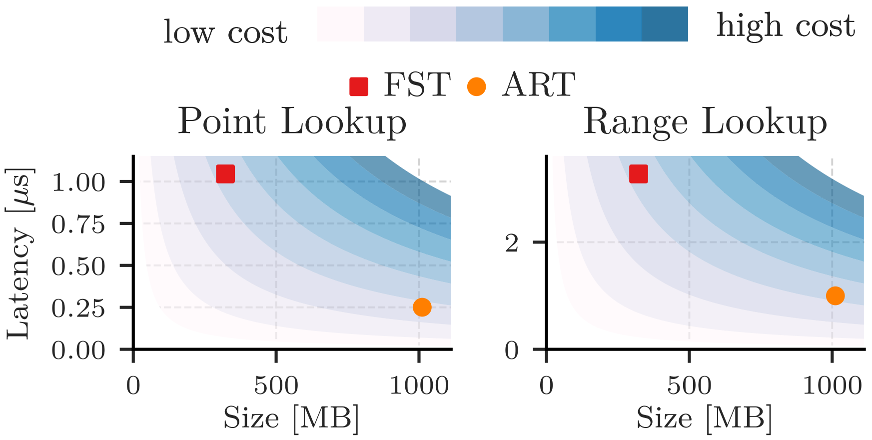


Evaluation: Hybrid Trie – Space & Performance



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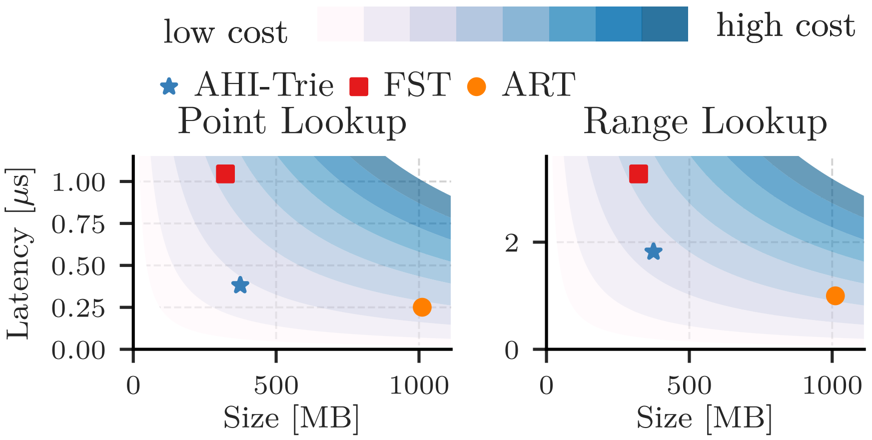

Conclusions:

For point lookups, Hybrid Trie

⇒ reduces index size by 63% comp. to ART

⇒ improves performance by 2.7x comp. to FST

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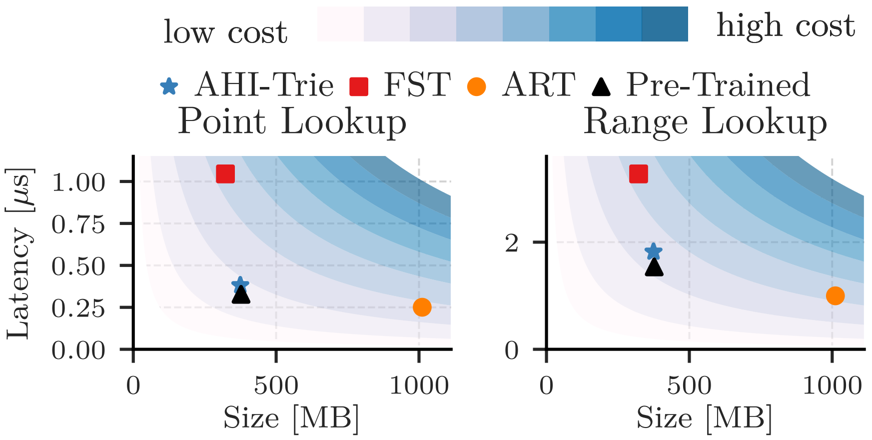

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The Pre-Trained Hybrid Trie does not include tracking-related overhead

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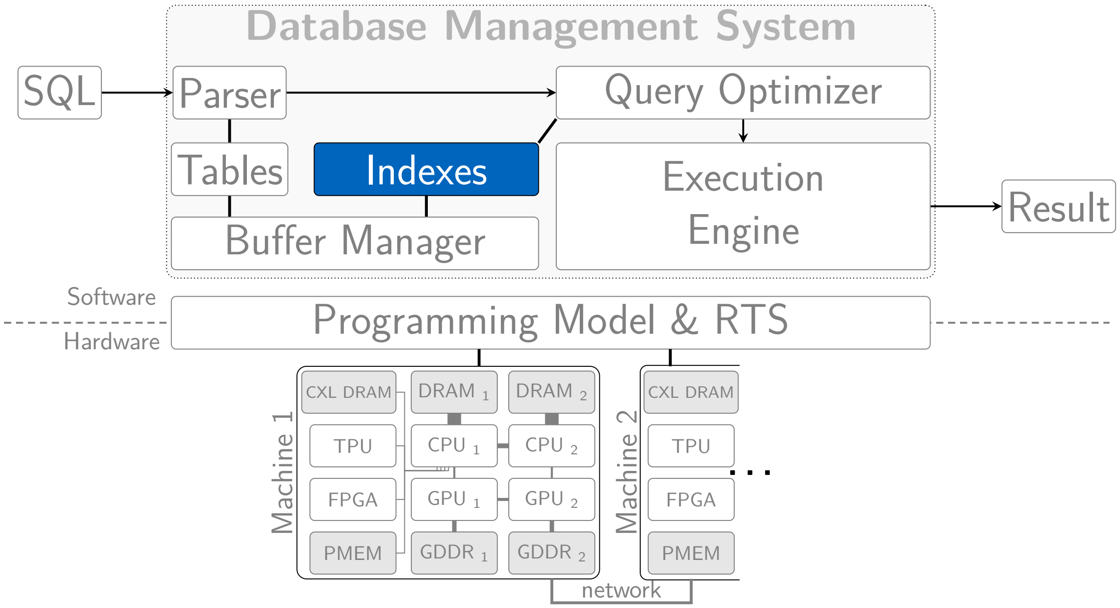

Adaptive Hybrid Indexes

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ABSTRACT

While index structures are crucial components in high-performance query processing systems, they occupy a large fraction of the available memory. Recently-proposed compact indexes reduce this space overhead and thus speed up queries by allowing the database to keep larger working sets in memory. These compact indexes, however, are slower than performance-optimized in-memory indexes because they adopt encodings that trade performance for memory efficiency. Applying different encodings within a single index might allow optimizing both dimensions at the same time – however, it is not clear which encodings should be applied to which index parts at *build-time*.

To take advantage of multiple encodings in *one* index structure, we present a new framework forming the basis of *workload-adaptive hybrid indexes* which moves encoding decisions to *run-time* instead. By sampling incoming queries adaptively, it tracks accesses to index parts and keeps fine-grained statistics which are used for space- and performance-optimized encoding migrations. We evaluated our framework using B+-trees and tries, and examine the adaptation process and space/performance trade-off for real-world and synthetic workloads. For skewed workloads, our framework can reduce the space by up to 82% while retaining more than 90% of the original performance.

CCS CONCEPTS

• **Information systems** → **Data access methods**; **Data layout**.

KEYWORDS

Space-efficient Index; Adaptive Index; Hybrid Index

ACM Reference Format:
Christoph Anneser, Andreas Kipf, Huanchen Zhang, Thomas Neumann, and Alfons Kemper. 2022. Adaptive Hybrid Indexes. In *Proceedings of the 2022 International Conference on Management of Data (SIGMOD '22), June 12–17, 2022, Philadelphia, PA, USA*. ACM, New York, NY, USA, 14 pages. https://doi.org/10.1145/3514221.3526121

ACM ISBN 978-1-4503-9249-5/22/06…$15.00
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Adaptation Manager
Queries
Aggregated Samples
D 13 reads, 1 write
B 2 reads, 0 writes
Classify Nodes
D → hot
B → cold
A B C D
① Track node accesses ② Compact cooling nodes ③ Expand hot nodes

Figure 1: Our sampling-based workload adaptation supports hybrid index structures in choosing the most suitable encoding for each part based on fine-grained access statistics at run-time. It supports user-defined settings such as an upper memory budget and it keeps sampling-related overhead limited by following an adaptive cost-optimized approach.

1 INTRODUCTION

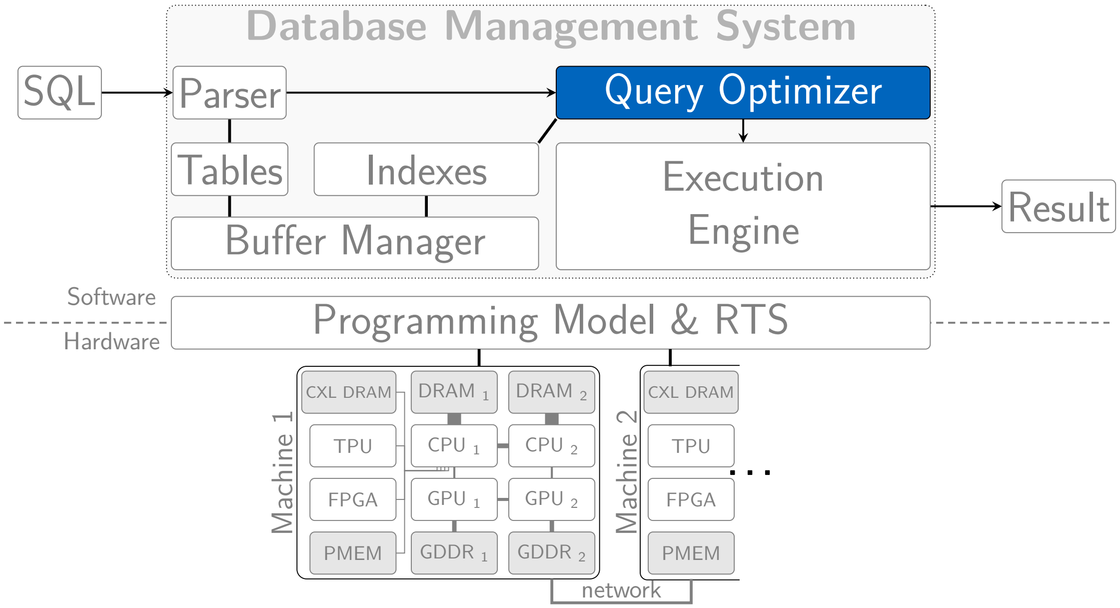
Back in 2006, Jim Gray stated that memory is the new disk and disk is the new tape [5]. This also applies to modern database systems that store the entire data in random access memory (RAM) to allow real-time analyses for trading companies and financial services, for example. They need to process large datasets efficiently to react to new developments and updates within a few milliseconds.

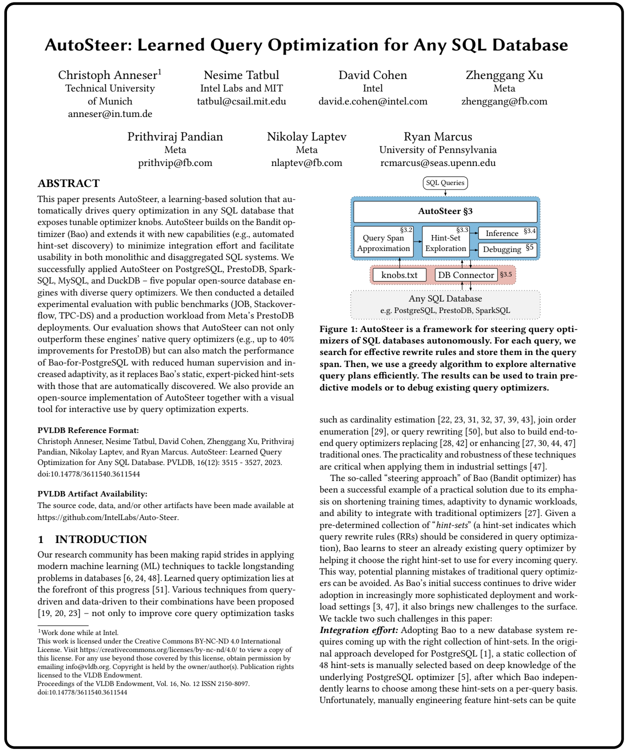
While the DRAM-prices have been stable during the last six to seven years, the data collected by sensors, smartphones, social media platforms, IoT-devices, and digital market-places *increases at a high rate* resulting in data overflows [54], and storing all data in memory becomes infeasible in many cases. However, as in-memory database systems become more and more popular for performance-critical businesses, AWS offers RAM instances that are optimized for in-memory database systems [1]. These instances are equipped with in-memory capacities of up to 24 TB, but the hourly cost of such an instance is more than $120.

To achieve high-performance query-processing for real-time analyses, index structures such as B-trees, tries, and hash tables are widely used by DBMSs. Because there might be multiple indexes per table, especially in OLTP DBMSs, the storage overhead for indexes can be significant. In many cases, more than half of the available memory of a DBMS can be attributed to index structures [54].

@SIGMOD'22

P2: AutoSteer





AutoSteer: Learned Query Optimization for Any SQL Database

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ABSTRACT

This paper presents AutoSteer, a learning-based solution that automatically drives query optimization in any SQL database that exposes tunable optimizer knobs. AutoSteer builds on the Bandit optimizer (Bao) and extends it with new capabilities (e.g., automated hint-set discovery) to minimize integration effort and facilitate usability in both monolithic and disaggregated SQL systems. We successfully applied AutoSteer on PostgreSQL, PrestoDB, SparkSQL, MySQL, and DuckDB – five popular open-source database engines with diverse query optimizers. We then conducted a detailed experimental evaluation with public benchmarks (JOB, Stackoverflow, TPC-DS) and a production workload from Meta's PrestoDB deployments. Our evaluation shows that AutoSteer can not only outperform these engines' native query optimizers (e.g., up to 40% improvements for PrestoDB) but can also match the performance of Bao-for-PostgreSQL with reduced human supervision and increased adaptivity, as it replaces Bao's static, expert-picked hint-sets with those that are automatically discovered. We also provide an open-source implementation of AutoSteer together with a visual tool for interactive use by query optimization experts.

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The so-called "steering approach" of Bao (Bandit optimizer) has been a successful example of a practical solution due to its emphasis on shortening training times, adaptivity to dynamic workloads, and ability to integrate with traditional optimizers [27]. Given a pre-determined collection of "*hint-sets*" (a hint-set indicates which query rewrite rules (RRs) should be considered in query optimization), Bao learns to steer an already existing query optimizer by helping it choose the right hint-set to use for every incoming query. This way, potential planning mistakes of traditional query optimizers can be avoided. As Bao's initial success continues to drive wider adoption in increasingly more sophisticated deployment and workload settings [3, 47], it also brings new challenges to the surface. We tackle two such challenges in this paper:

Integration effort: Adopting Bao to a new database system requires coming up with the right collection of hint-sets. In the original approach developed for PostgreSQL [1], a static collection of 48 hint-sets is manually selected based on deep knowledge of the underlying PostgreSQL optimizer [5], after which Bao independently learns to choose among these hint-sets on a per-query basis. Unfortunately, manually engineering feature hint-sets can be quite

Figure 1: AutoSteer is a framework for steering query optimizers of SQL databases autonomously. For each query, we search for effective rewrite rules and store them in the query span. Then, we use a greedy algorithm to explore alternative query plans efficiently. The results can be used to train predictive models or to debug existing query optimizers.

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Many Database Management Systems expose tunable optimizer knobs.

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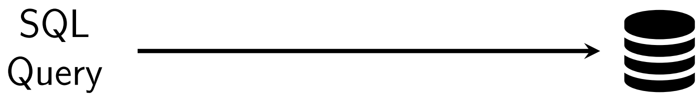

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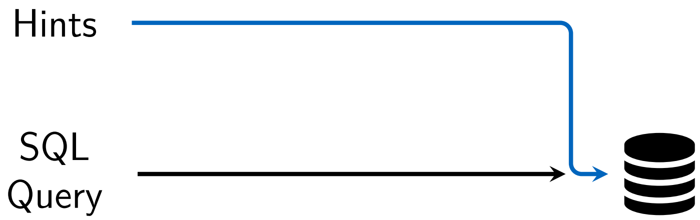

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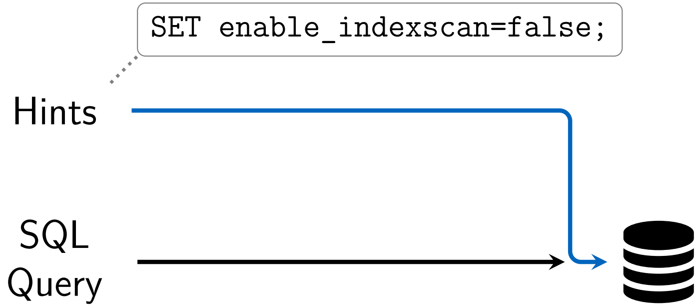

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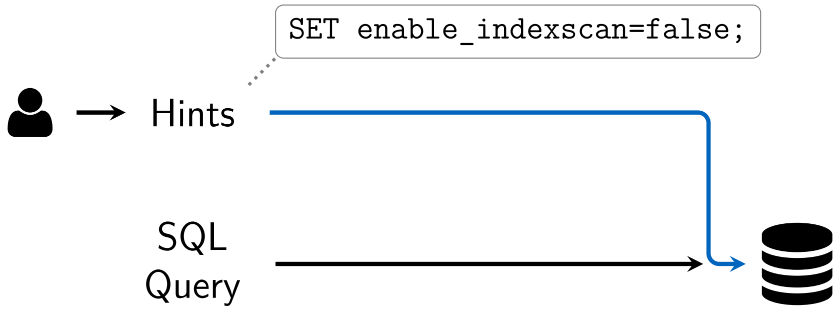

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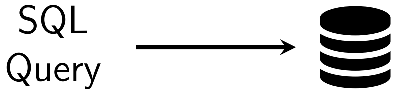

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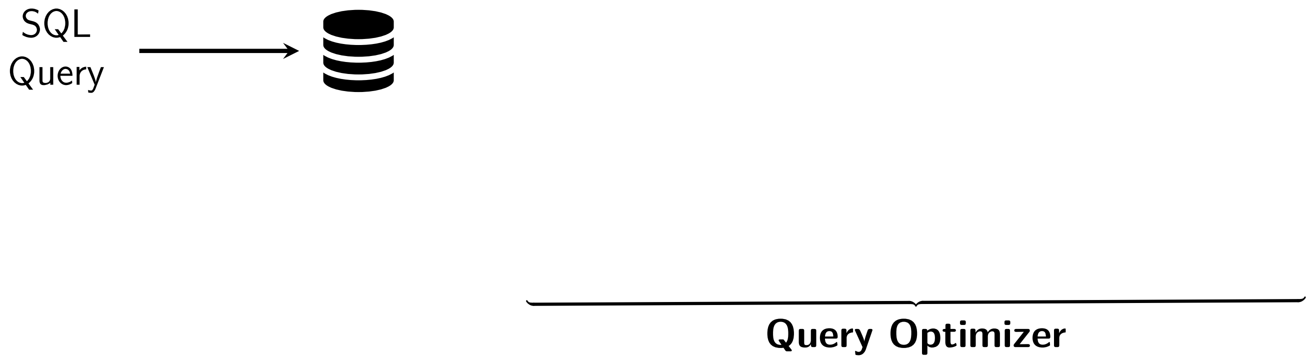

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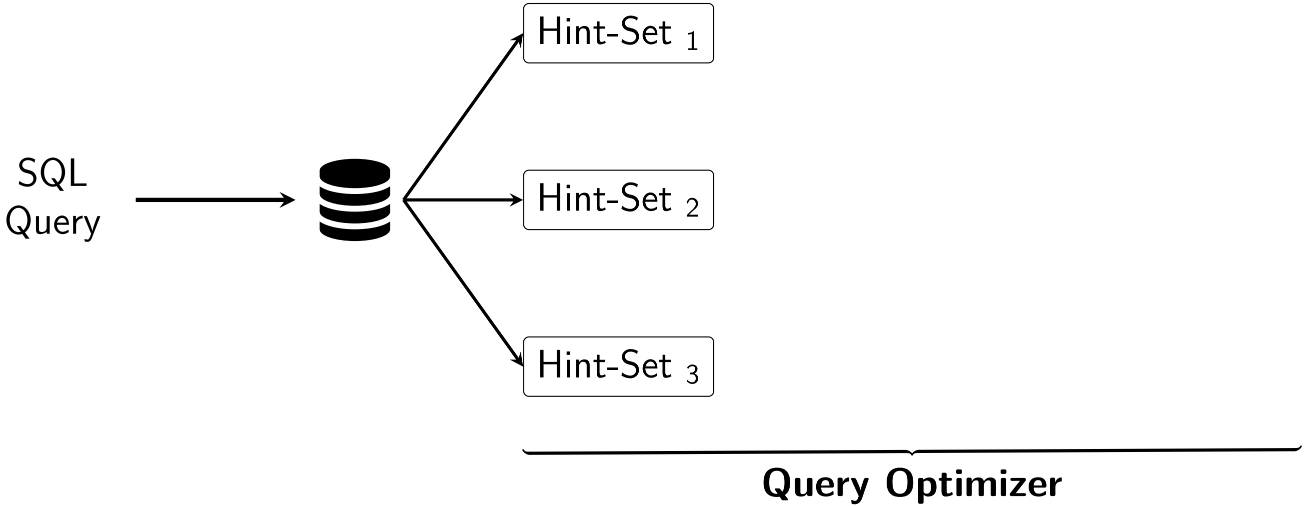

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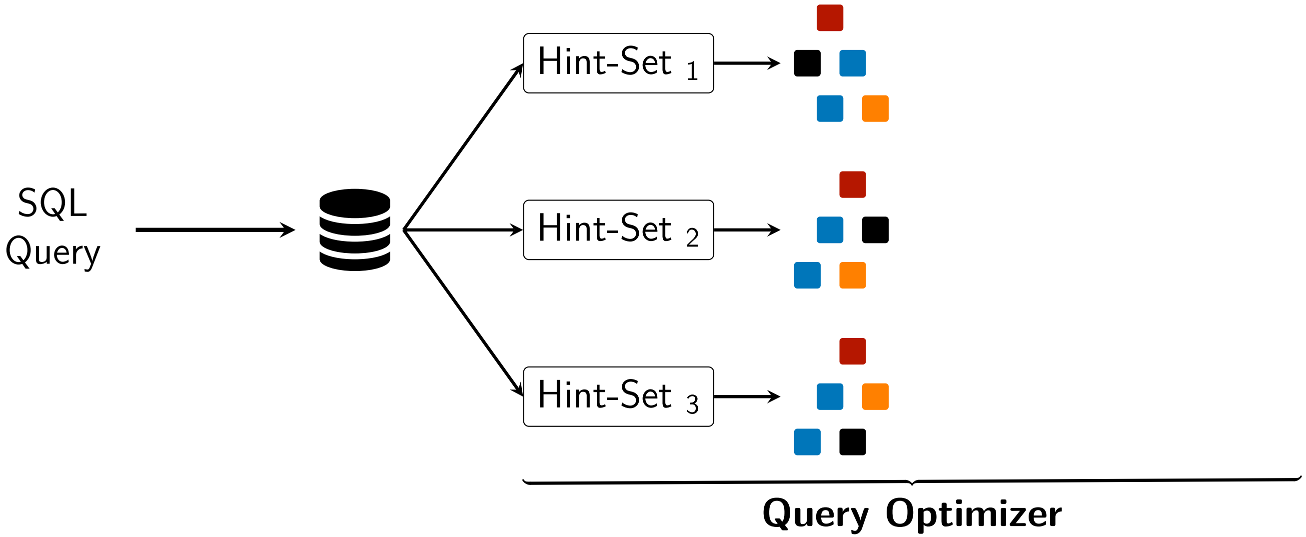

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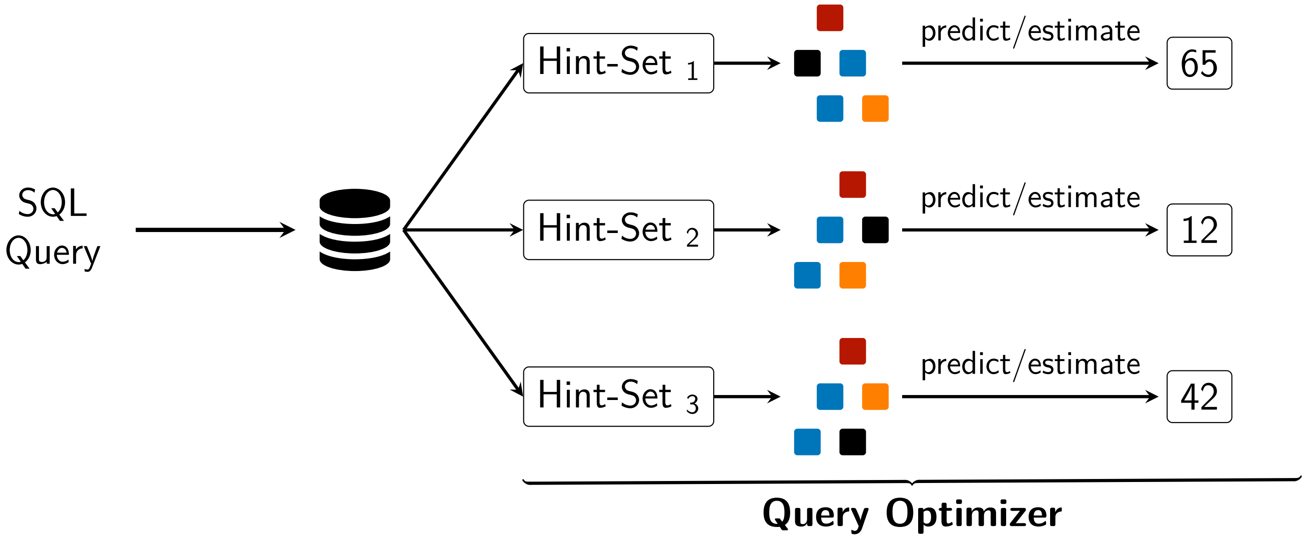

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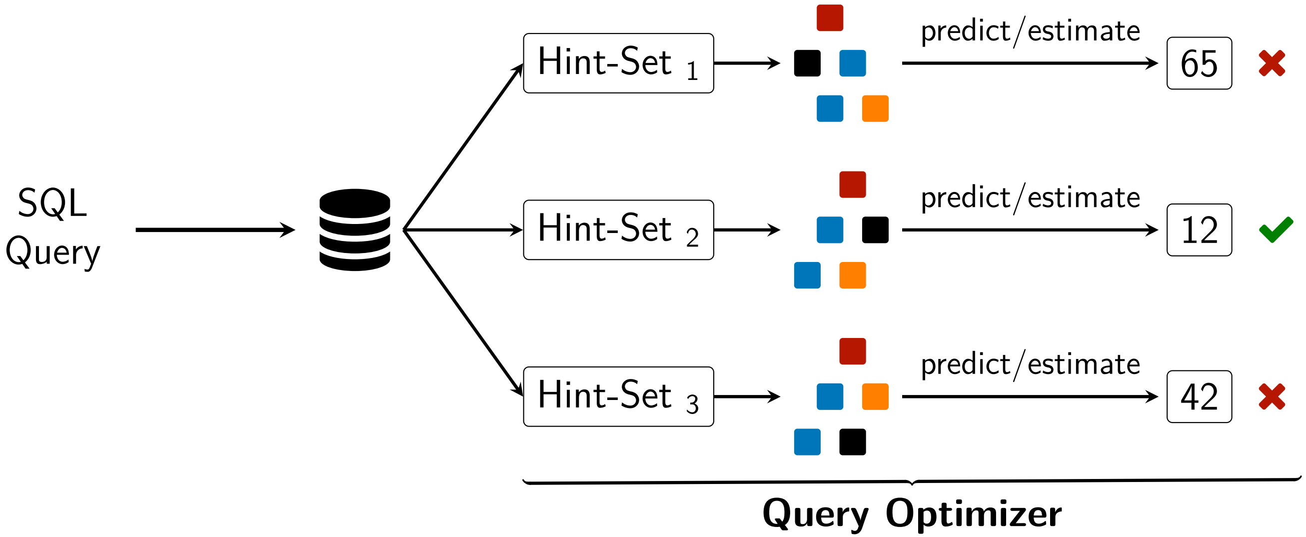

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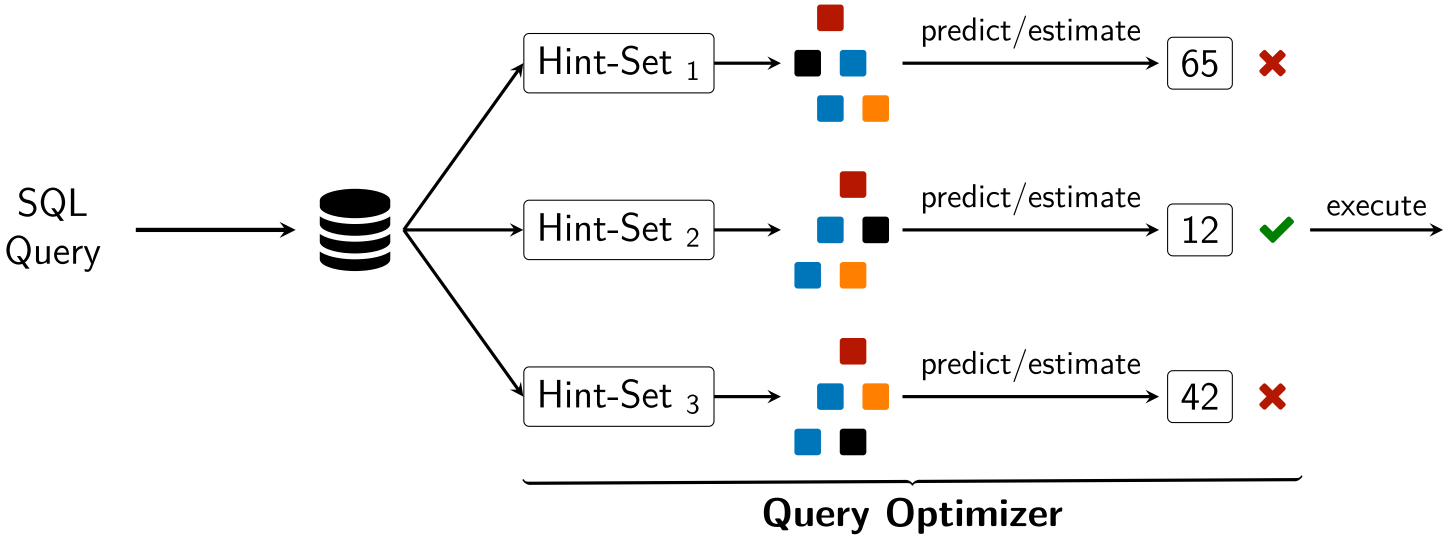

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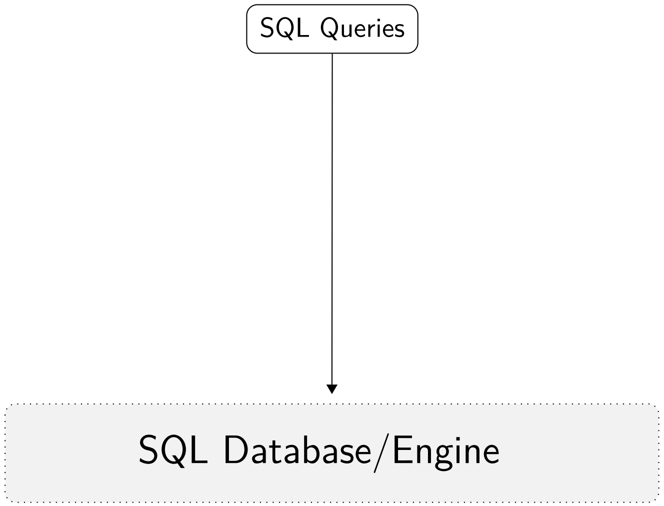

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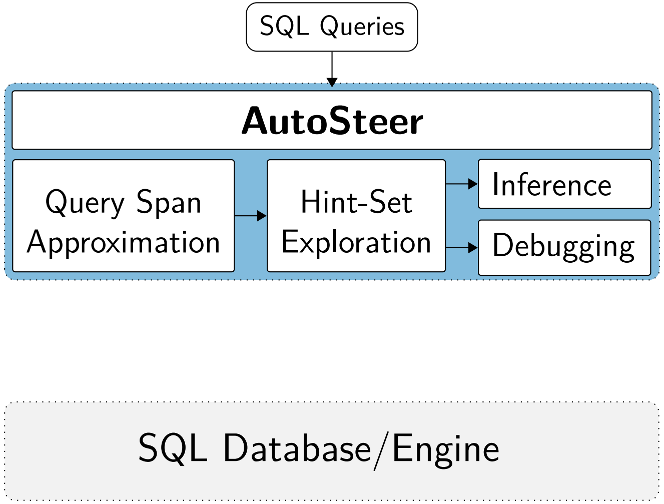

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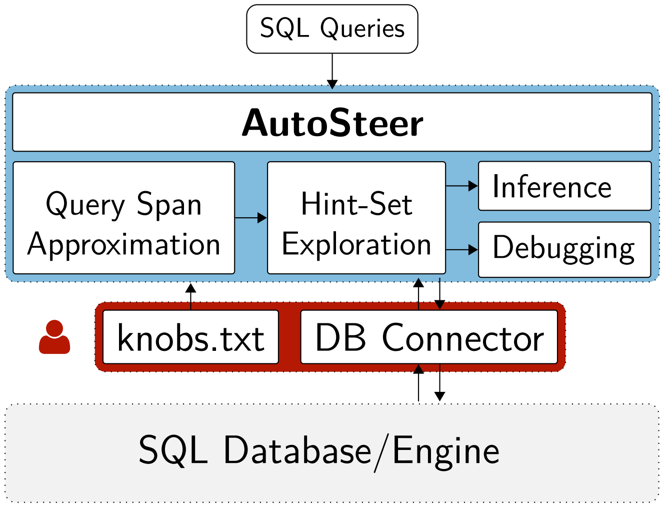

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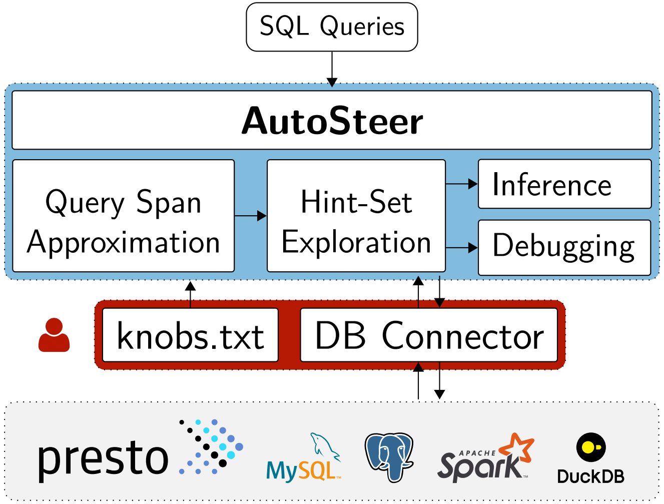

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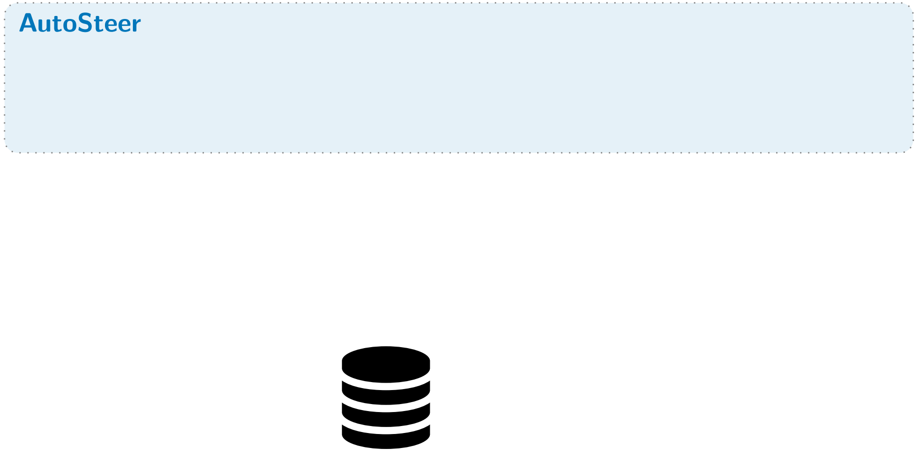
AutoSteer – Overview



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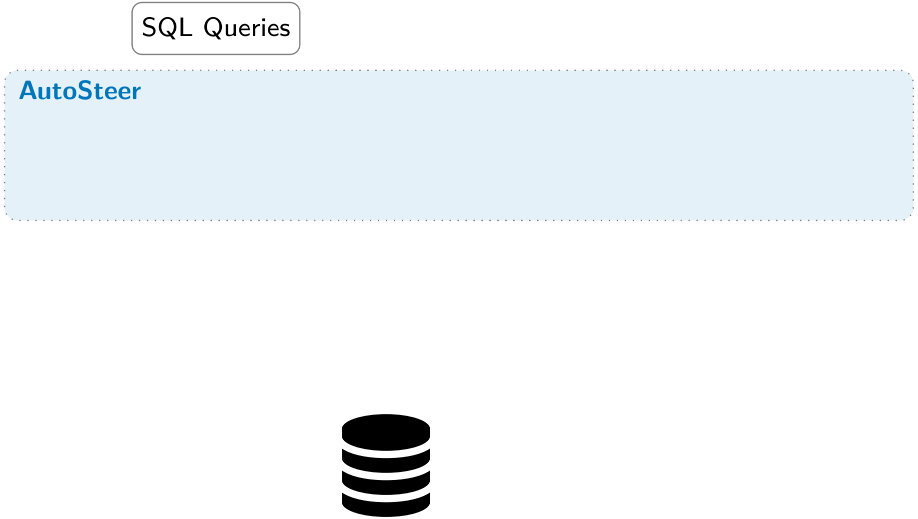

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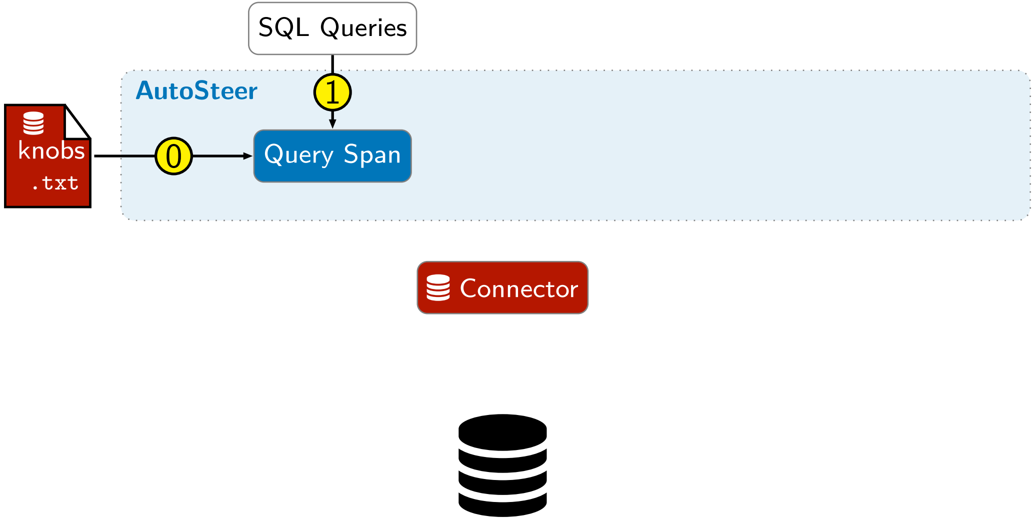

A **Query Span** contains all knobs that affect the query's optimization!

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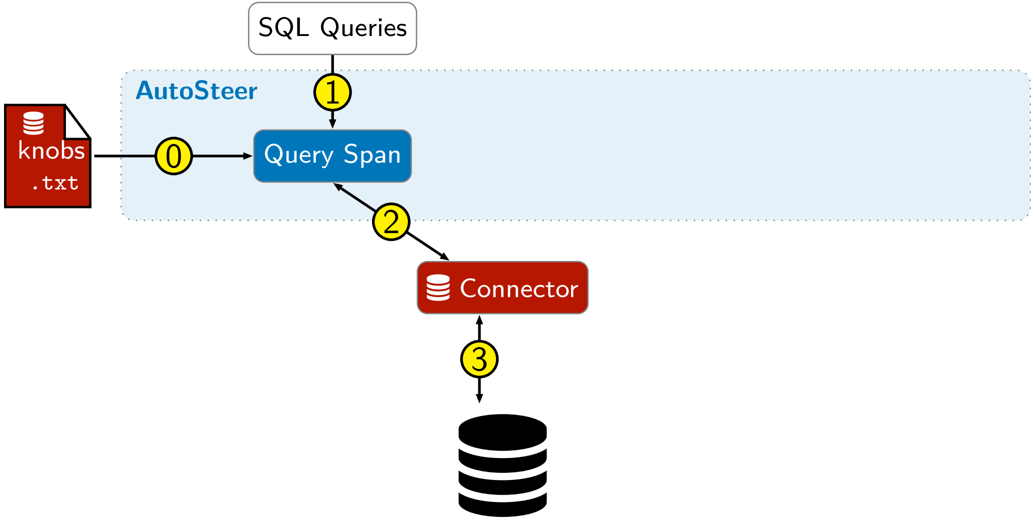

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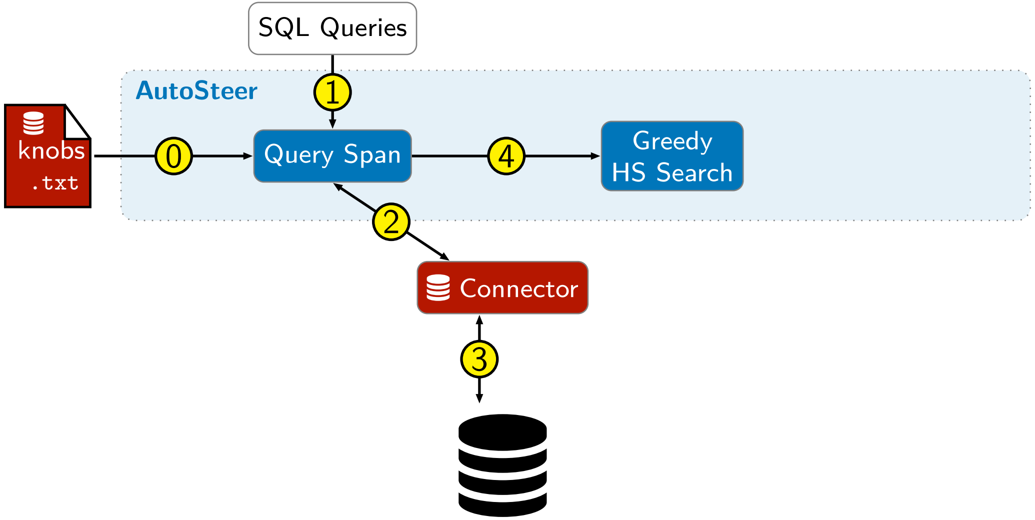

The **greedy search** aims at finding the top hint-sets for a query.

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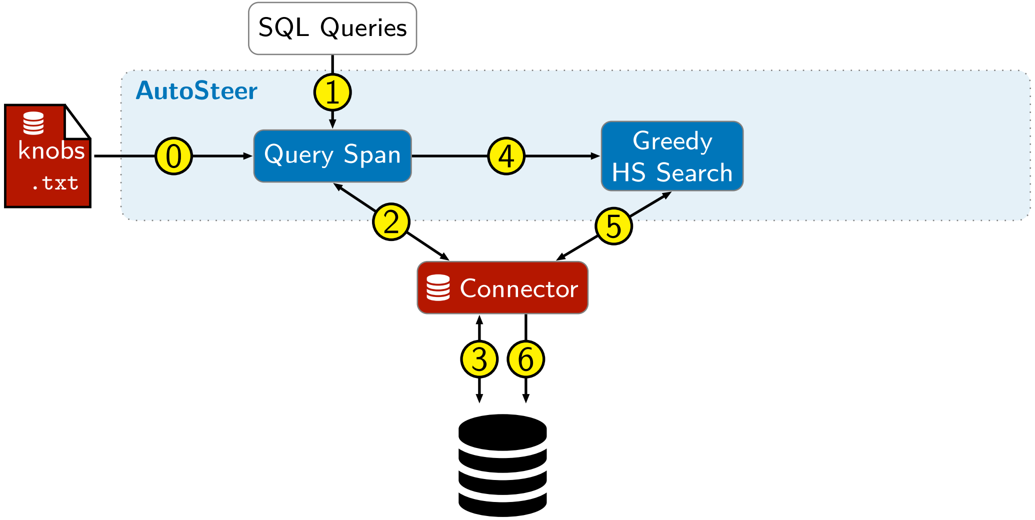

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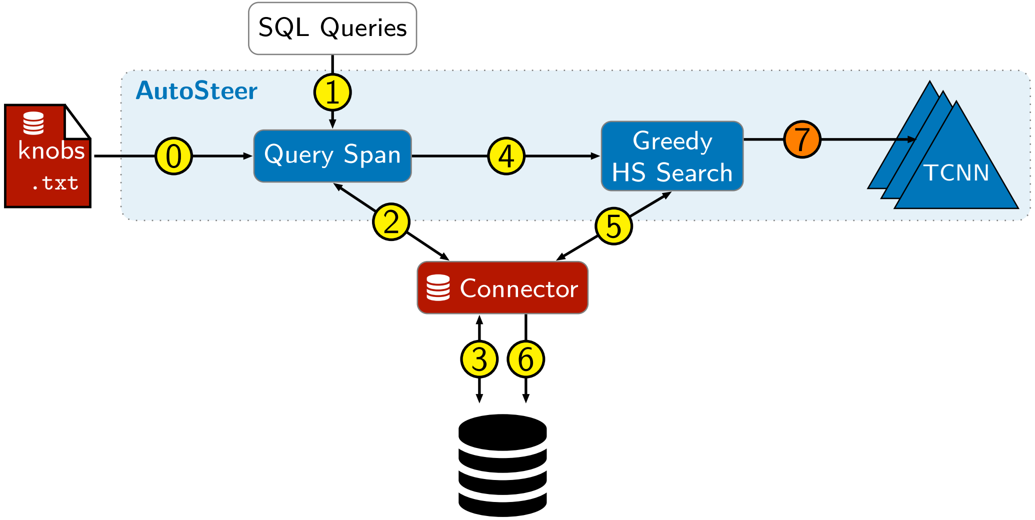

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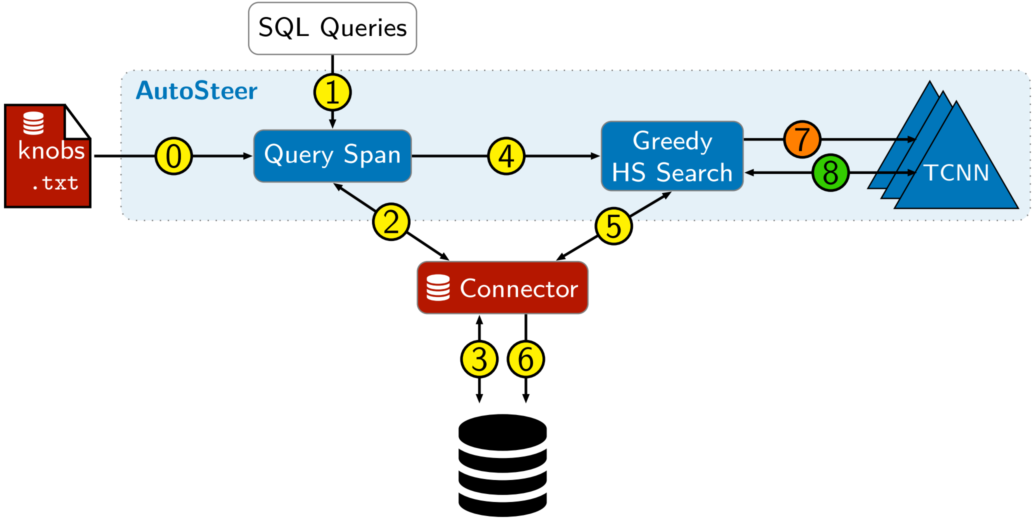

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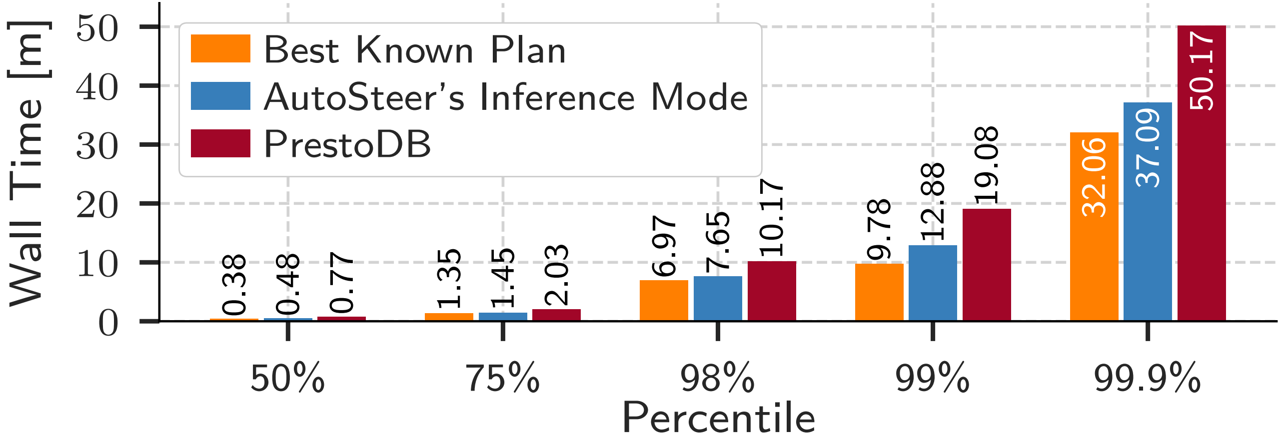
Inference Mode

AutoSteer **steers queries at runtime** and uses the TCNN to **infer execution times**.

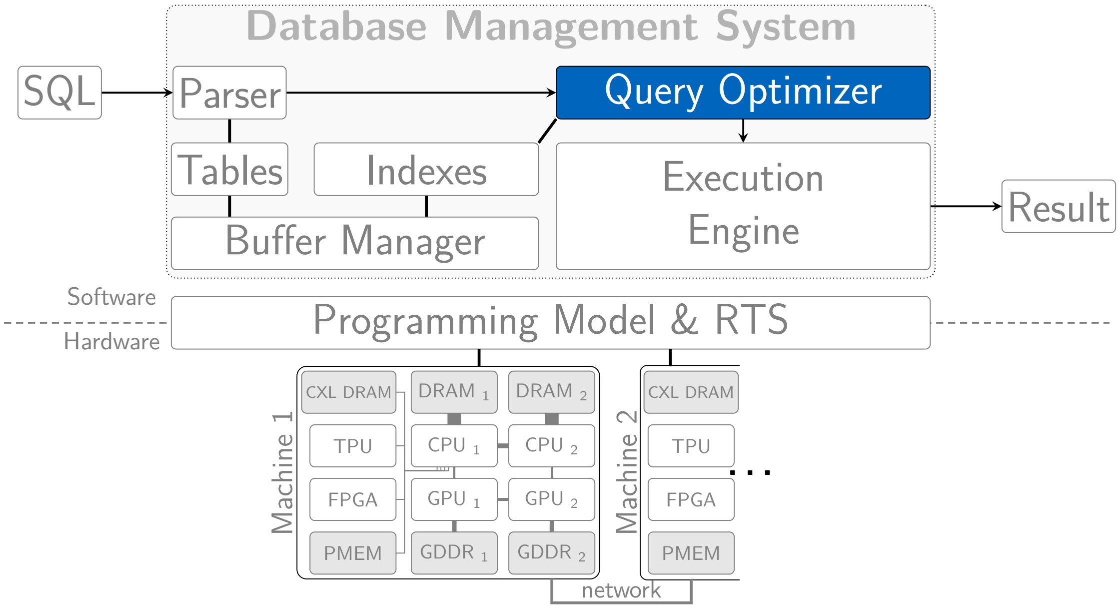
Dashboard Application at Meta – PrestoDB

- Focus on **tail latencies**
- >3000 Queries, scanning PBs of data, hundreds of worker nodes
- Workload runs multiple times per day



AutoSteer significantly reduces tail latencies of production workloads at Meta

P2: AutoSteer



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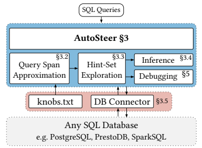

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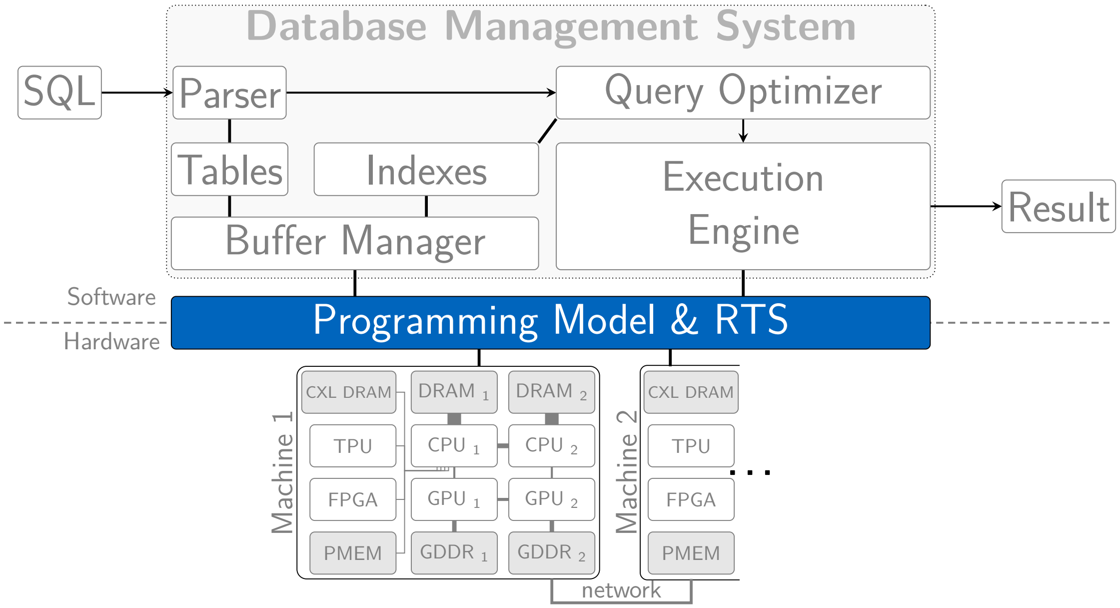
P3: Programming Fully Disaggregated Systems



Programming Fully Disaggregated Systems

Christoph Anneser Lukas Vogel Ferdinand Gruber
Maximilian Bandle Jana Giceva
Technical University of Munich
firstname.lastname@in.tum.de

Abstract

With full resource disaggregation on the horizon, it is unclear what the most suitable *programming model* is that enables dataflow developers to fully harvest the potential that recent hardware developments offer. In our vision, we propose to raise the abstraction level to allow developers to primarily reason about their dataflow and the requirements that need to be met by the underlying system in a declarative fashion. Underneath, the system works with typed memory regions and uses the notion of ownership that allows for more flexible memory management across the different compute devices and the tasks mapped onto them. This requires a holistic approach that crosses multiple layers of the system stack, opening exciting systems research questions.

ACM Reference Format:
Christoph Anneser, Lukas Vogel, Ferdinand Gruber, Maximilian Bandle, and Jana Giceva. 2023. Programming Fully Disaggregated Systems. In *Workshop on Hot Topics in Operating Systems (HOTOS '23), June 22–24, 2023, Providence, RI, USA*. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3593856.3595889

1 Introduction

With the ever-increasing demand for data, where the datasphere volume is expected to reach 175ZB by 2025 [50], we have reached the point where moving data is the dominating cost factor in data centers [34, 45]. Cloud providers race to serve the different requirements of modern workloads better but with pressure to achieve it in a more sustainable fashion [51]. To improve efficiency, data centers have evolved to more loosely coupled software-defined racks, where they disaggregate resources over fast network interconnects [52].

However, until recently, coherent memory remained tightly coupled, and servers had to be equipped with large memory capacities to serve peak workloads reliably. This

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(a) Current Architectures (b) Our Vision

Figure 1: Moving from a compute-centric to a memory-centric architecture.

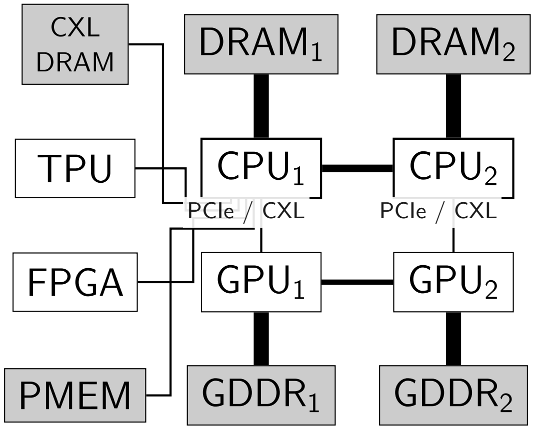
overprovisioning is a considerable cost (50% of Azure's servers [5] and 40% of Meta's rack costs come from memory [40]) for a resource that could not be properly pooled. The average memory utilization reported by many cloud vendors remains low, typically in the range of 50-65% [38, 56]. Therefore, data centers could reduce costs by pooling different types of memory [9, 11, 21, 57] and compute devices [6, 13, 17–19, 30, 33, 47] by connecting them with fast networks [14, 45].

However, data and compute placement within these pools significantly impacts the overall system performance. For example, non-uniform memory accesses (NUMA) can slow down algorithms by up to 3× [39]. Similarly, a naïve data placement in a heterogeneous storage landscape can reduce a database system's performance by up to 3× [59].

Moreover, today, optimal placement has become an issue even *within* single processors. For example, take the recently introduced Intel's 4th Generation Intel® Xeon® Scalable Processors – codenamed *Sapphire Rapids* [7]. They have built-in encryption, compression, streaming, and high-bandwidth memory accelerators. Its most promising feature, however, is the adoption of Compute Express Links™ (CXL™) – an industry standard for cache-coherent interconnects for processors, memory expansion, and accelerators based on PCIe 5.0, which has been adopted by companies like Intel, AMD, ARM, Samsung, and NVIDIA, amongst others [9]. CXL enables us to first *scale-up* nodes by extending their compute and memory pools with 'pluggable' compute devices and DRAM/PMem expansion cards before we have to rely on more expensive 'scale-outs' to other compute nodes that

@HotOS'23

Motivation



CXL DRAM
DRAM1
DRAM2
TPU
CPU1
CPU2
PCIe / CXL
PCIe / CXL
FPGA
GPU1
GPU2
PMEM
GDDR1
GDDR2

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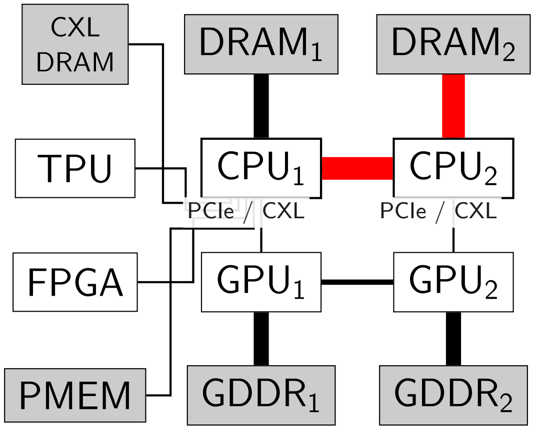
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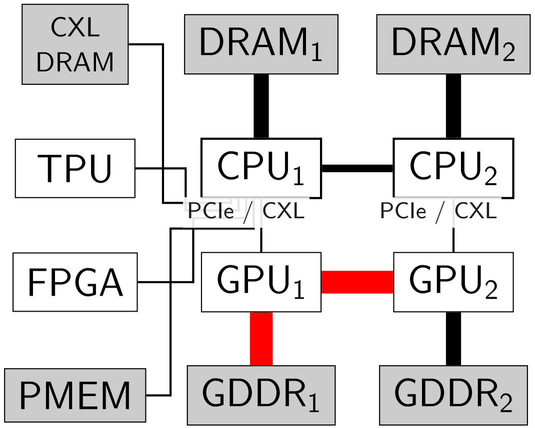
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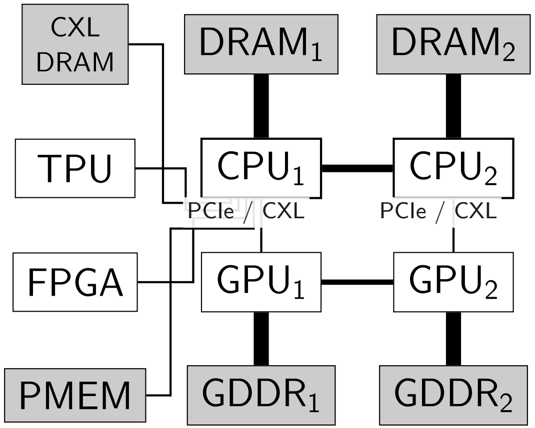

Name	Bw.	Lat.	Gran.	Attached	Sync	Persist.
Cache	++	++	1 B	CPU	✓	✗
HBM	++	+	64 B	CPU	✓	✗
DRAM	+	+	64 B	CPU	✓	✗
PMem	○	○	256 B	CPU	✓	✓
CXL-DRAM	○	○	64 B	PCIe	✓/ ✗	✓/ ✗
Disagg. Mem.	○	–	?	NIC	✗	✓/ ✗
SSD	–	–	4 KiB	PCIe	✗	✓
HDD	– –	– –	4 KiB	SATA	✗	✓

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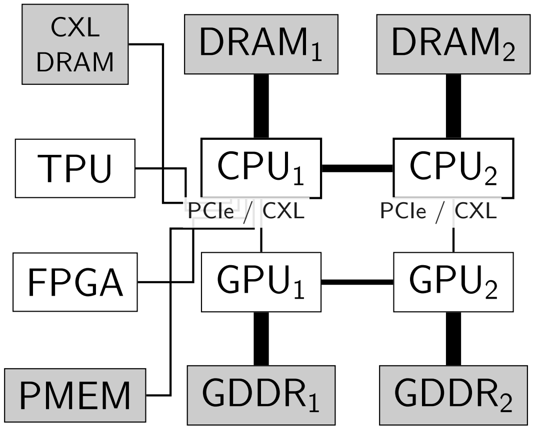

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How to develop & optimize software for heterogeneous, disaggregated hardware?

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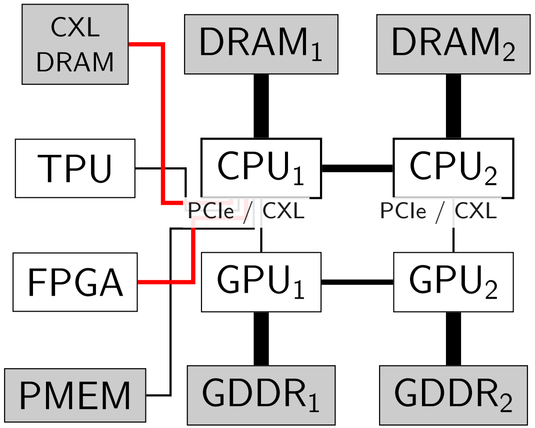

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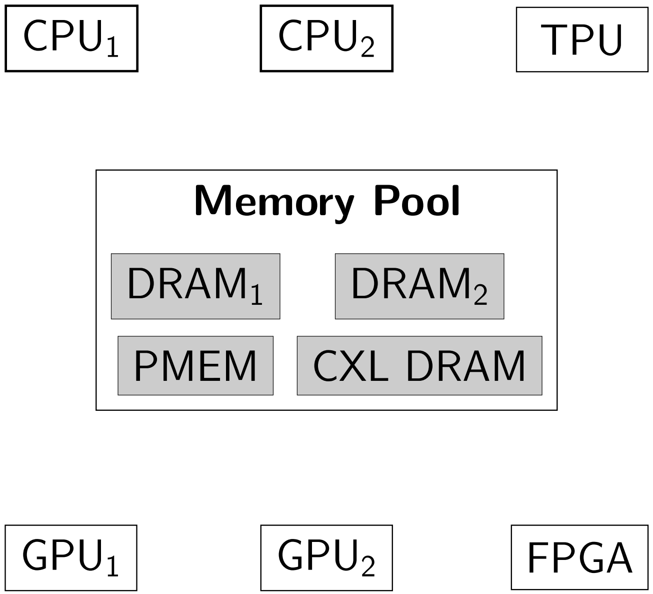

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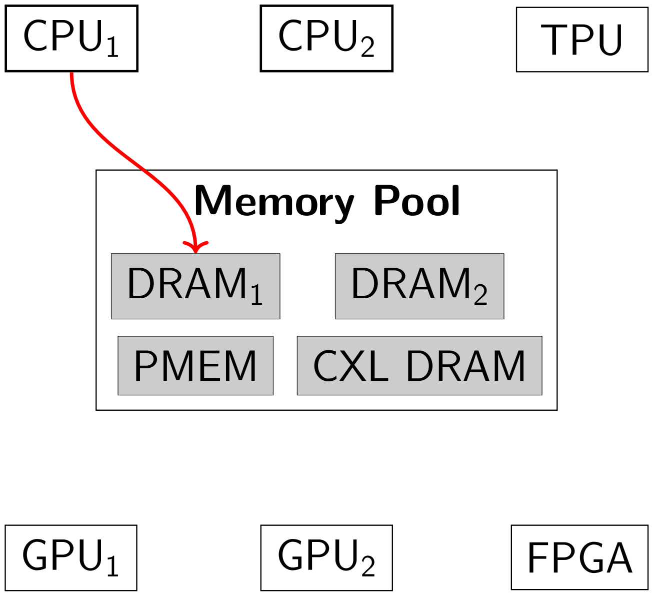

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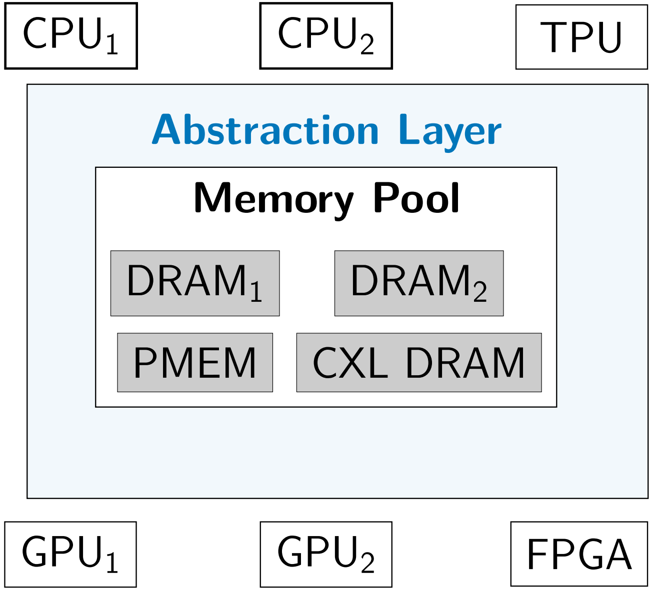

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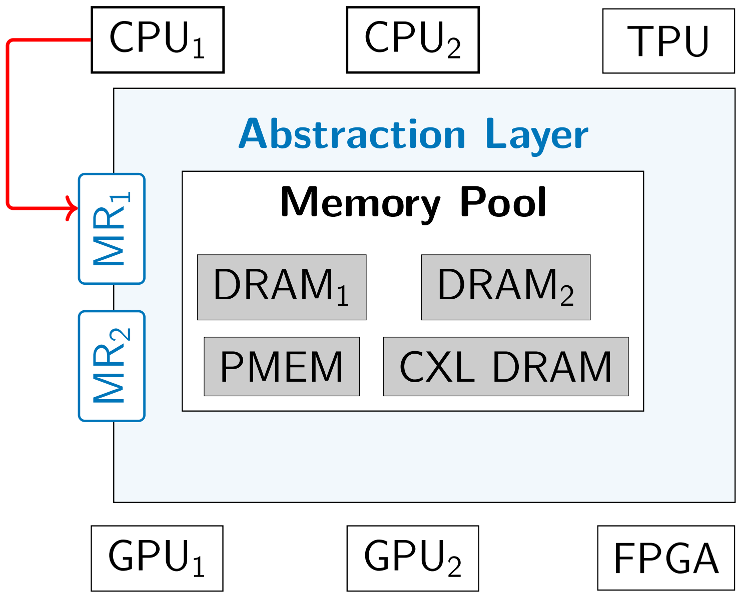

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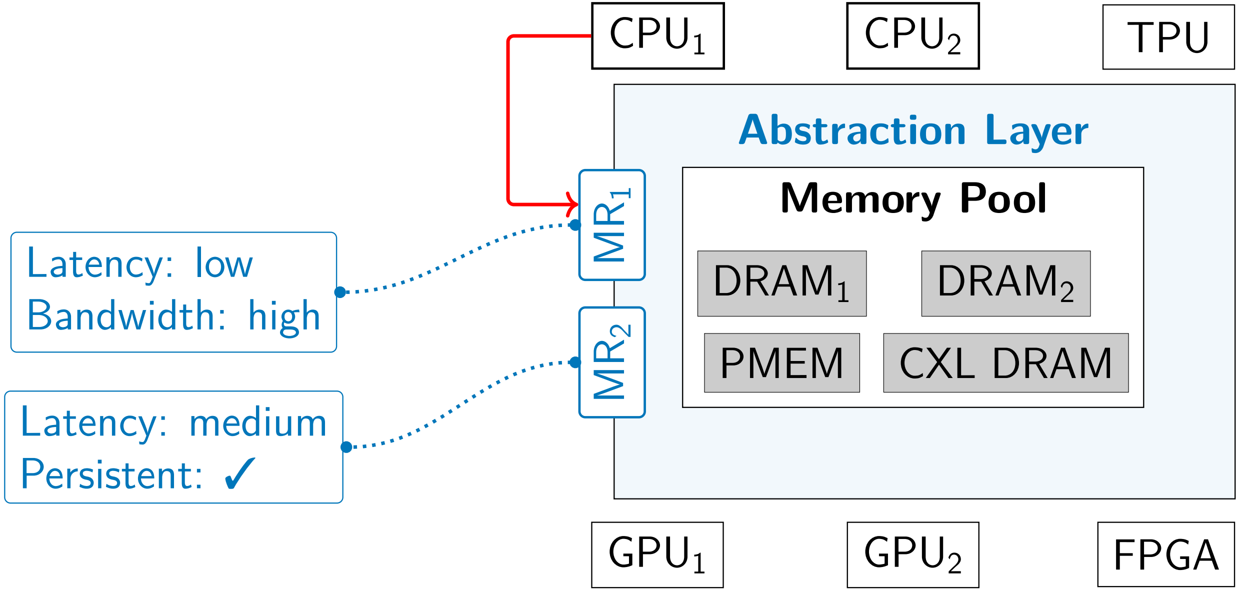

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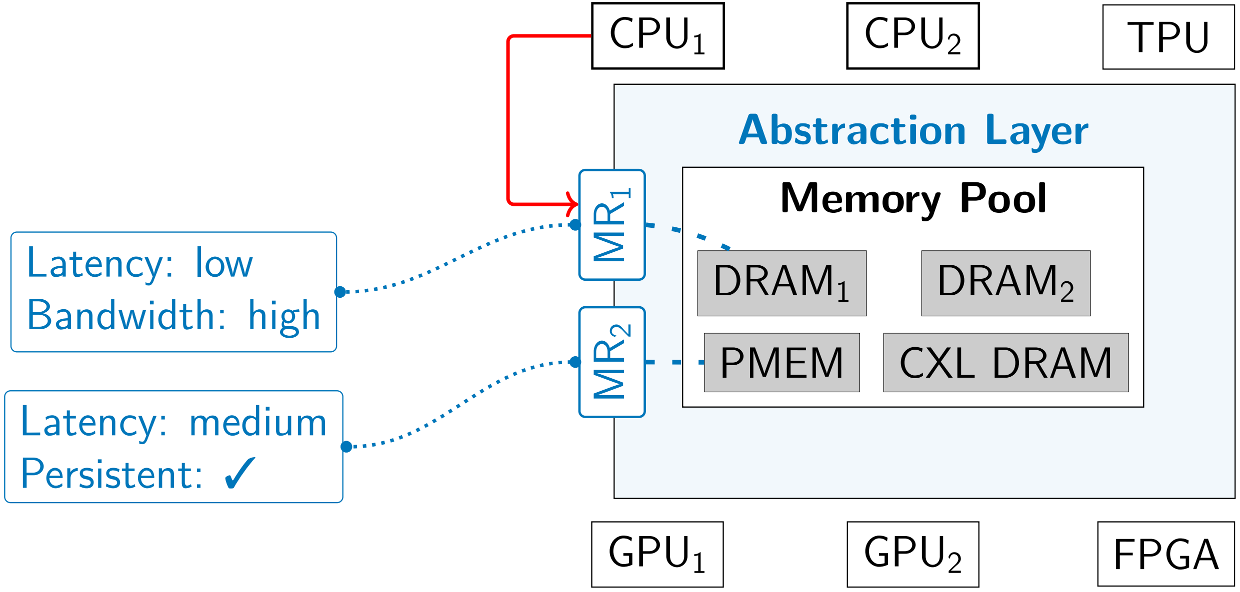

Mapping Memory Regions to Devices

⇒ **Task Placement**

Task 0 → Task 1 → Task 2

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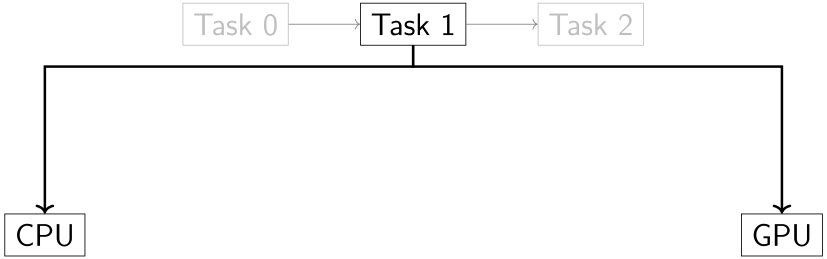

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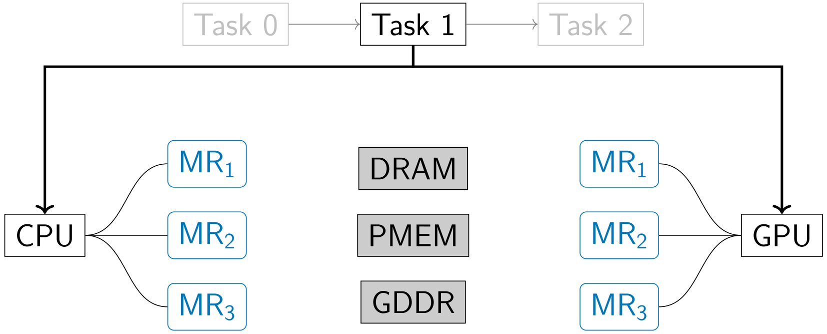

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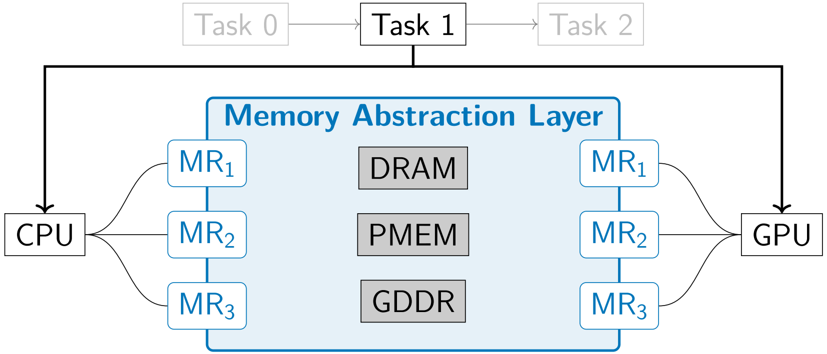

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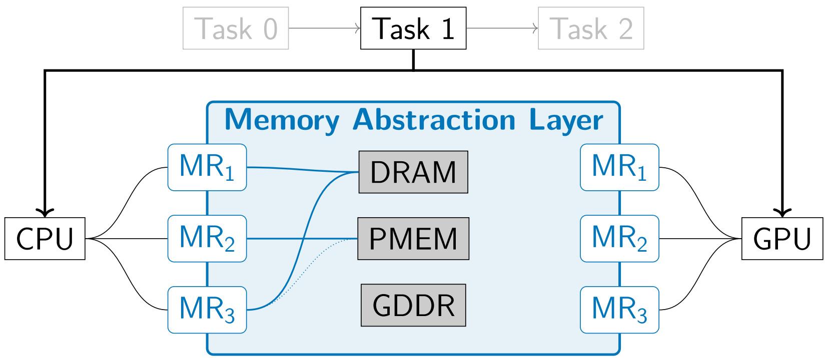

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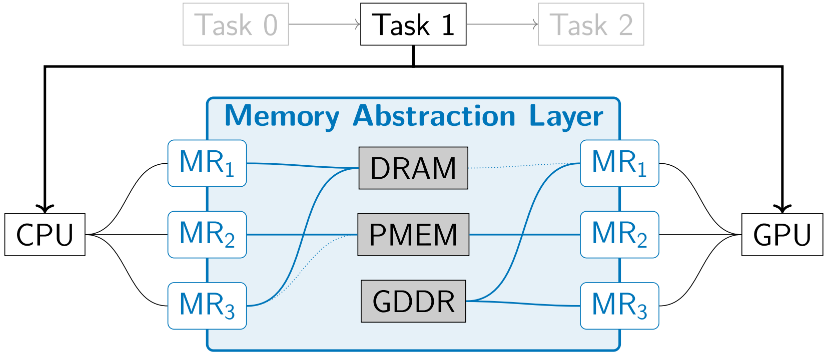

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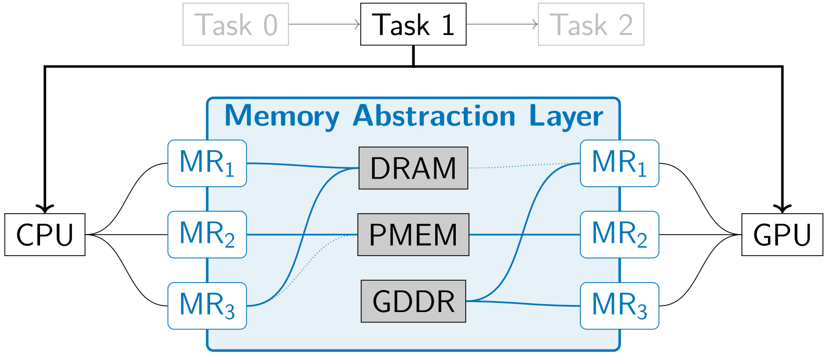

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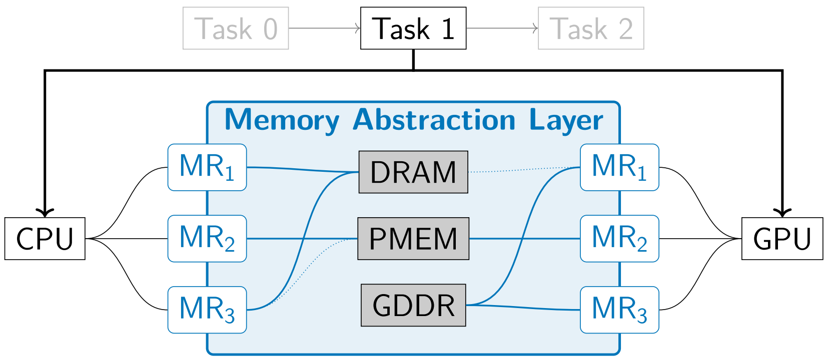

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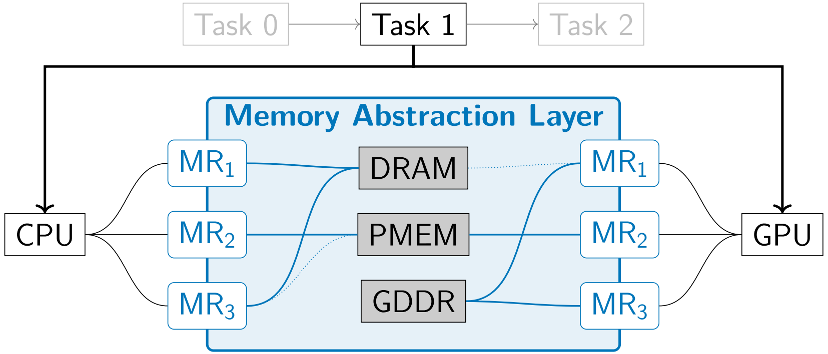

$ RTS needs a comprehensive cost model and late binding

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- Purpose: Syncing tasks, message passing, ...
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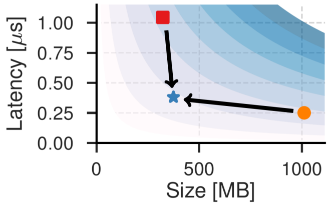
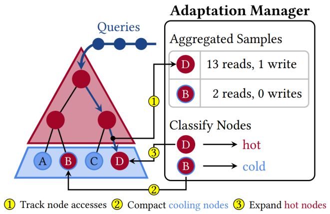
Private Scratch

Conclusions

Adaptive Hybrid Indexes reduce storage overheads & retain high-performance





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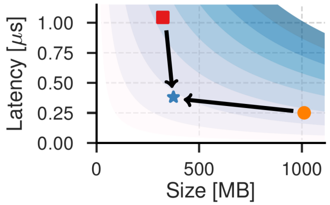
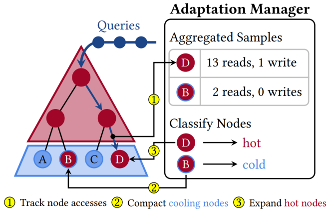
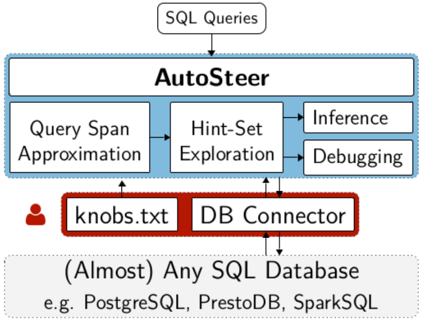
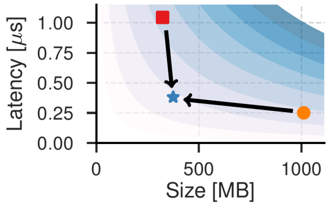


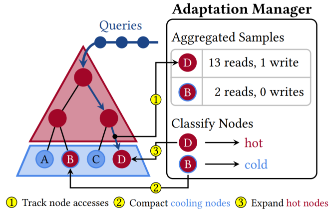




AutoSteer is a framework to steer rule-based query optimizers

Conclusions





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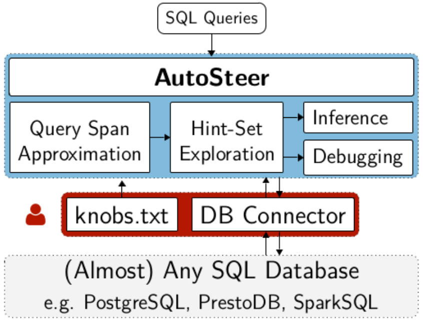

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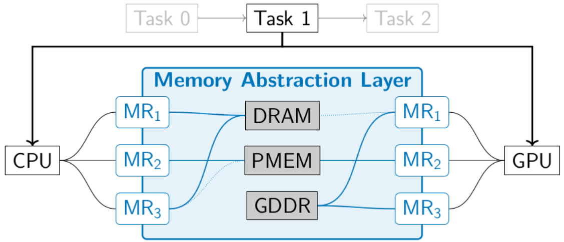
Memory-centric programming model for disaggregated memory



Questions?

Thank you for your attention!