Accelerating String-key Learned Index Structures via Memoization-based Incremental Training

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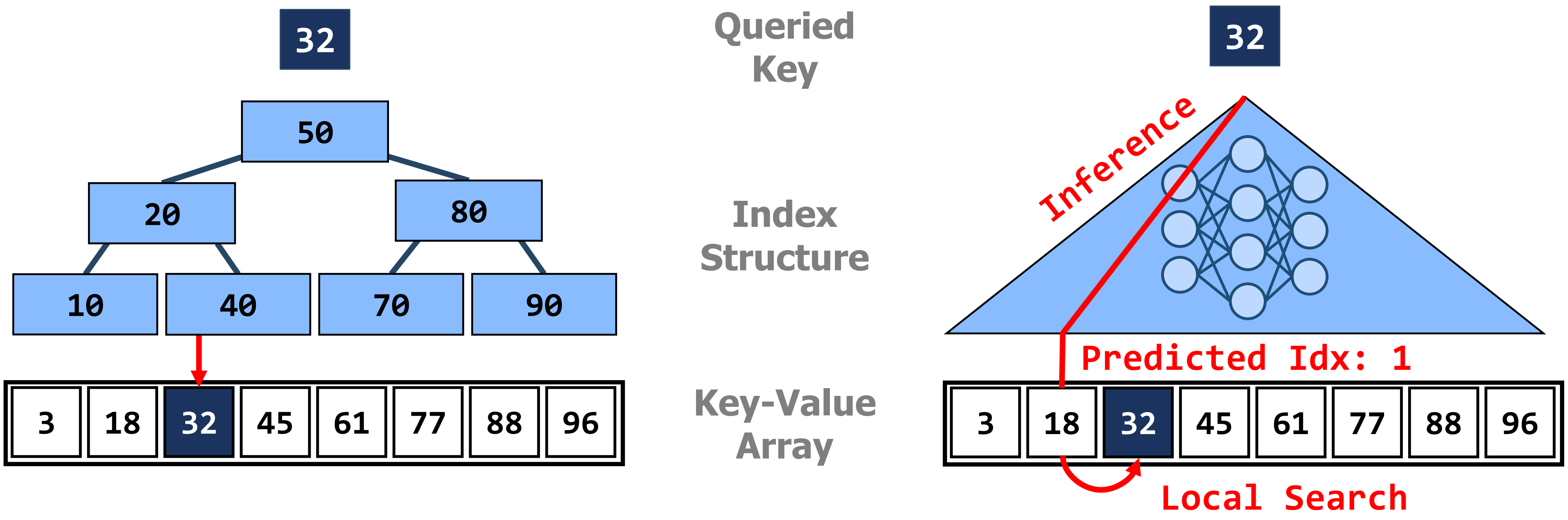
Learned Index Structure

Traditional Index Structure

Learned Index Structure

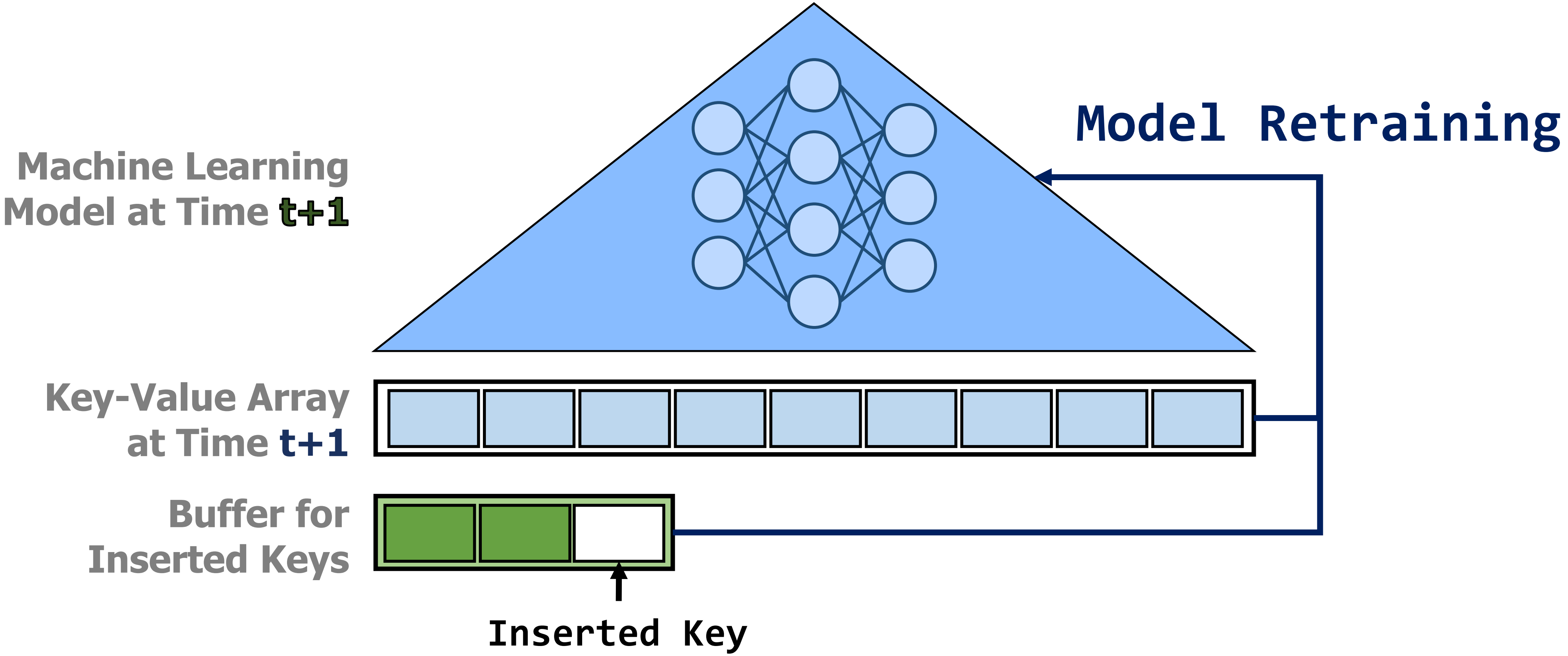


Learned Index Structure

	Traditional Index	Learned Index
Time Complexity	▲	▼
Performance	▼	▲
Index Size	▲	▼

- **Example Applications**
  - **Database**: BOURBON (2020)
    Learned Bigtable (2020)
  - **DNA Sequencing**: BLESS (2024)
  - **Embedded Sensor**: SENSORNETS (2023)

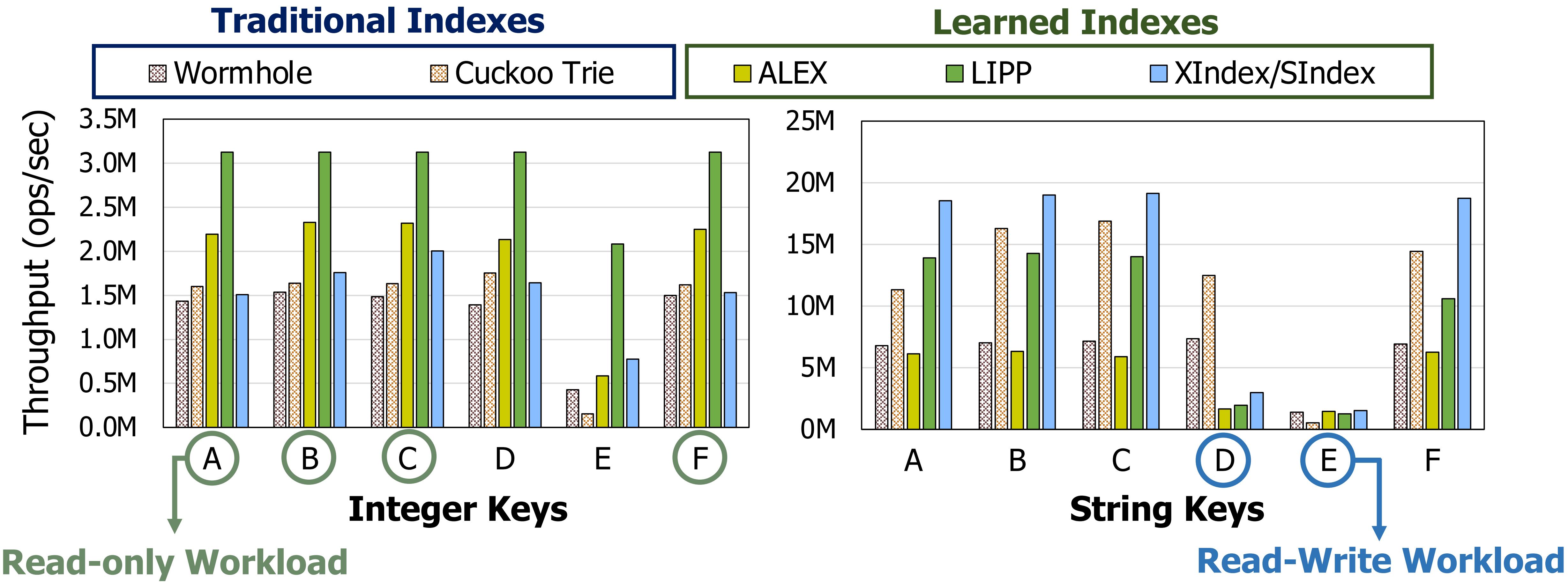
Updatable Learned Index



Updatable learned indexes require periodic retraining using the **entire keys**

Performance of Updatable Indexes

** Used YCSB (Yahoo Cloud Serving Benchmark) workloads*



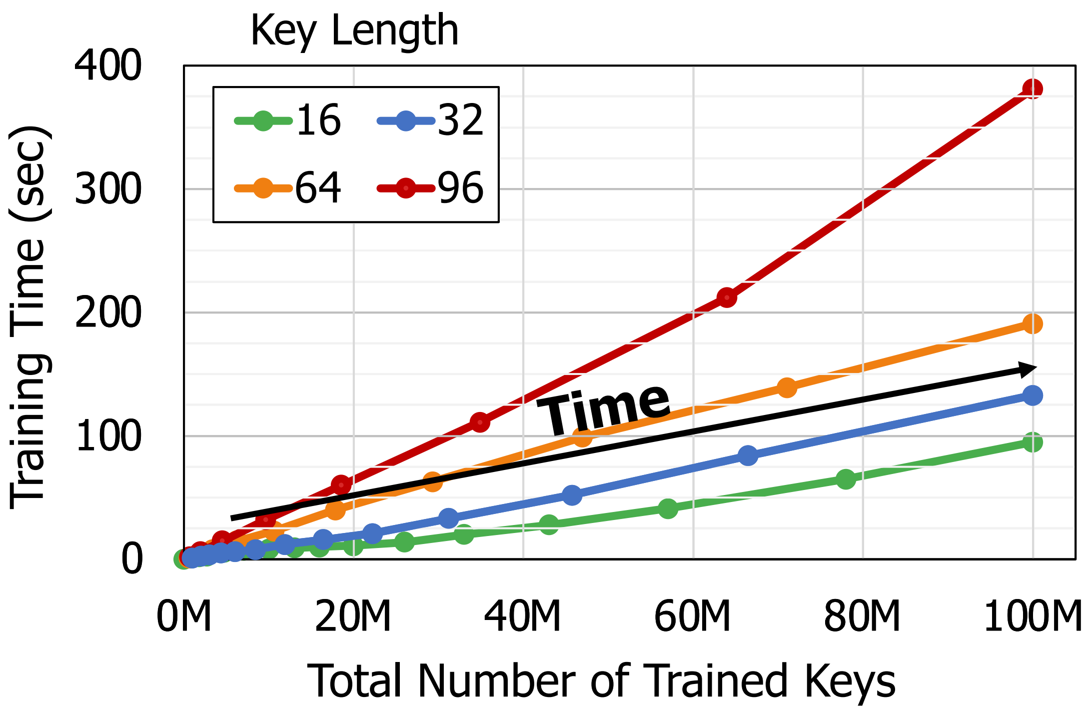
String-key learned indexes show **poor performance** for **read-write workloads**

Bottlenecks of Learned Index Training

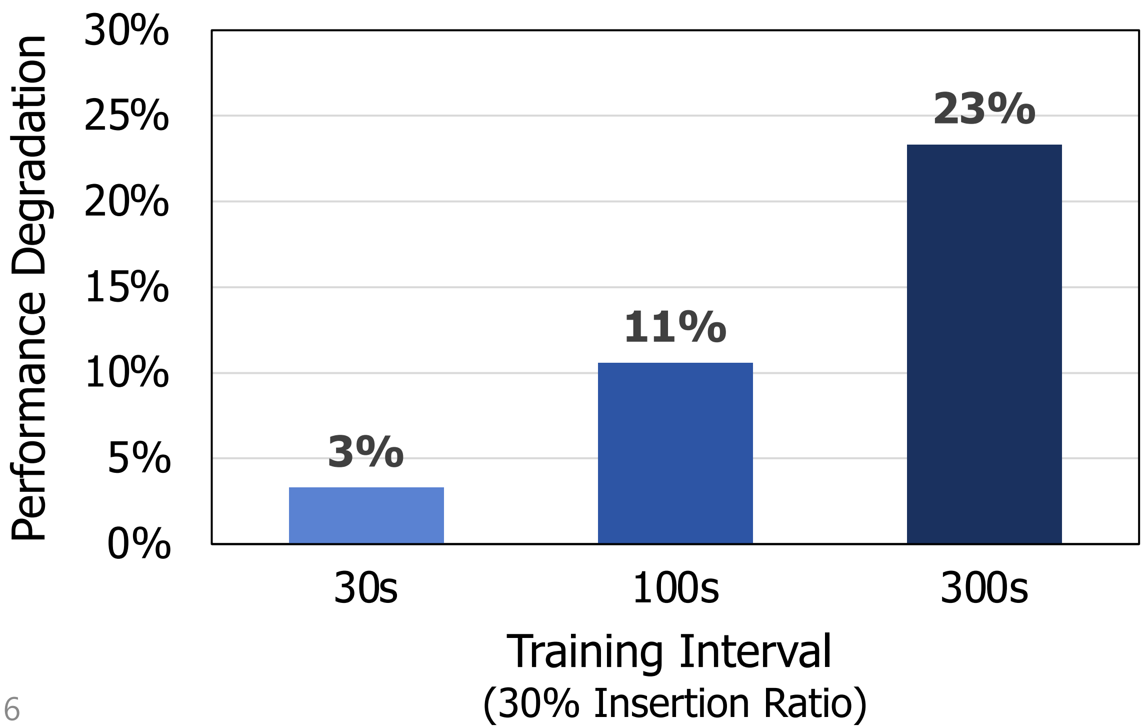
1. Bad scalability & performance due to accumulated keys

Accumulated keys **degrade the performance** of learned index by delaying updates of ML model

Increasing Training Time



Performance Degradation with Slow Training



Bottlenecks of Learned Index Training

2. QR Decomposition Operations are Expensive

- Most learned indexes use **linear regression** for their ML model
- Solving linear regression involves **QR decomposition**

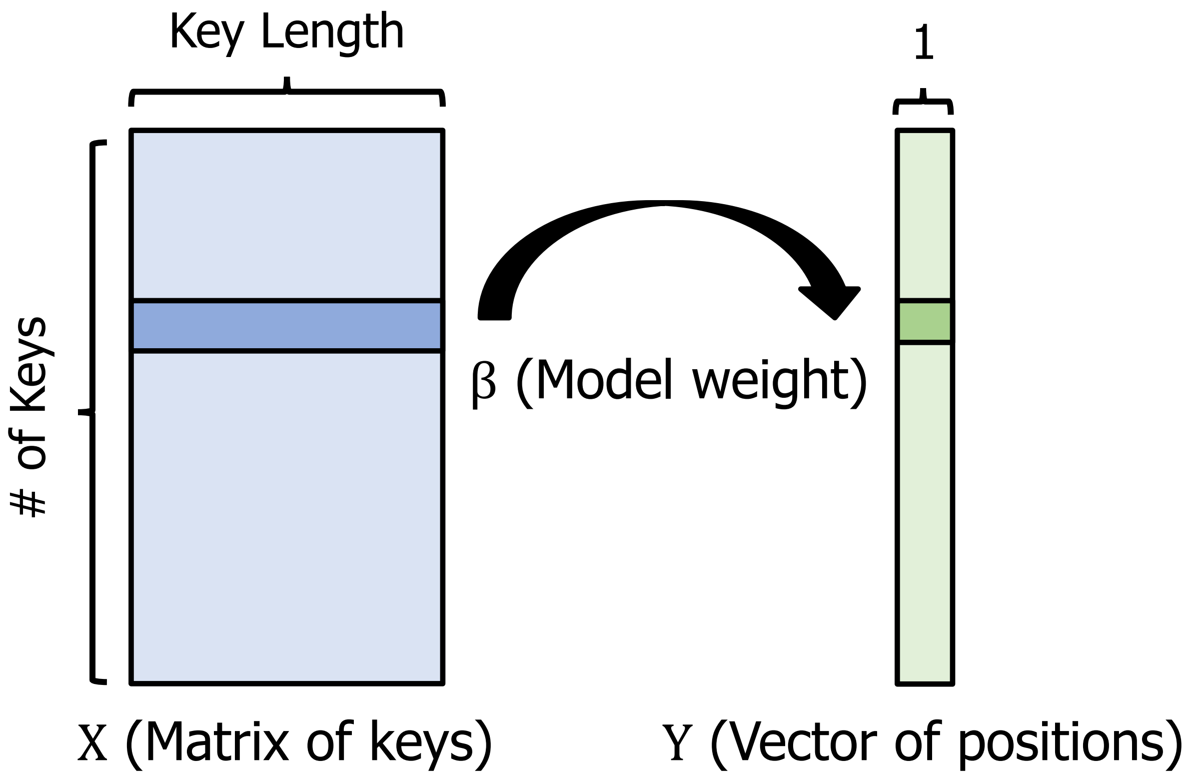
Linear Regression Model

$$X\beta = Y$$

Linear Regression Solution

$$\beta = \left(\mathbf{R}^{-1}\mathbf{R}^{-1^{T}}\right)X^{T}Y$$

, where $\mathbf{X} = \mathbf{QR}$



Bottlenecks of Learned Index Training

2. QR Decomposition Operations are Expensive

- **QR decomposition** is the major bottleneck when training
- **R Inverse and GEMM** are the second longest

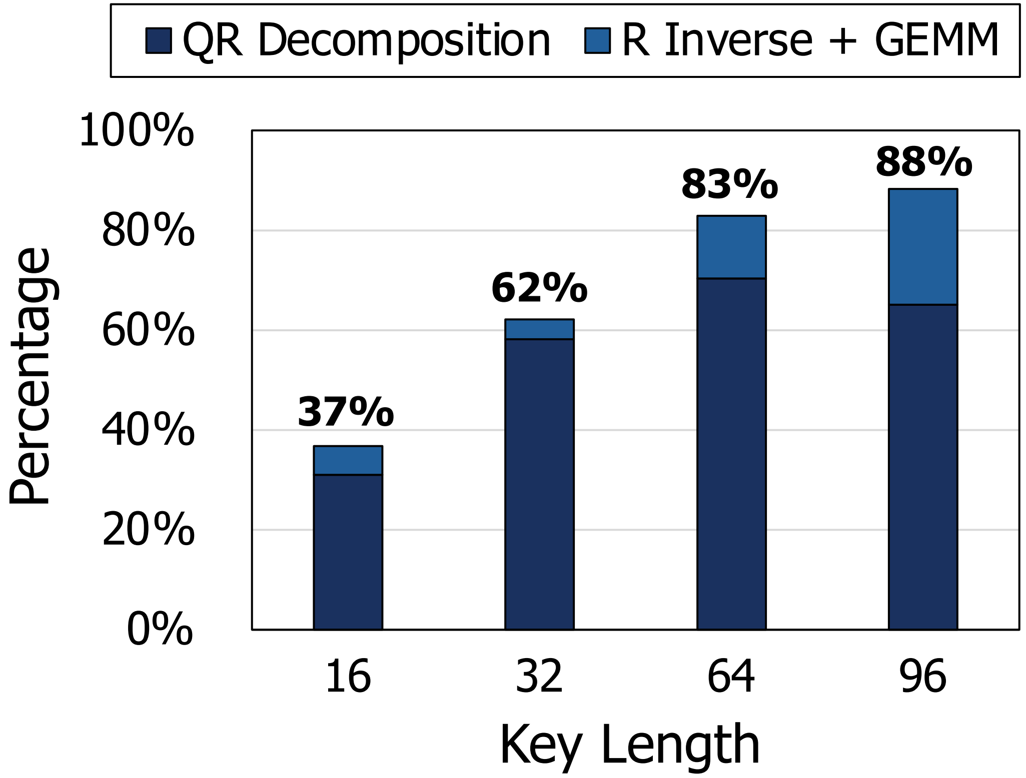
Linear Regression Model

$$X\beta = Y$$

Linear Regression Solution

$$\beta = \left(\mathbf{R}^{-1}\mathbf{R}^{-1^{T}}\right) X^{T} Y$$

, where $\mathbf{X} = \mathbf{QR}$



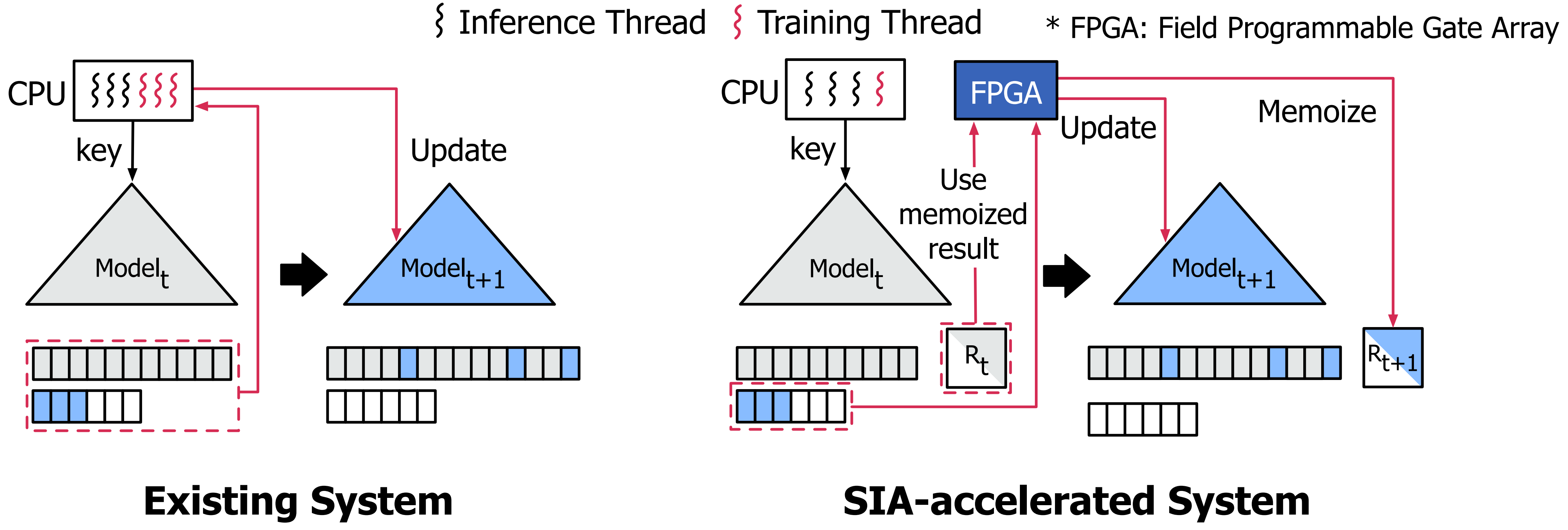
Existing String-key Learned Index Systems Offer Limited Performance

SIA: System Overview

Algorithm-Hardware Co-designed String-key Learned Index System

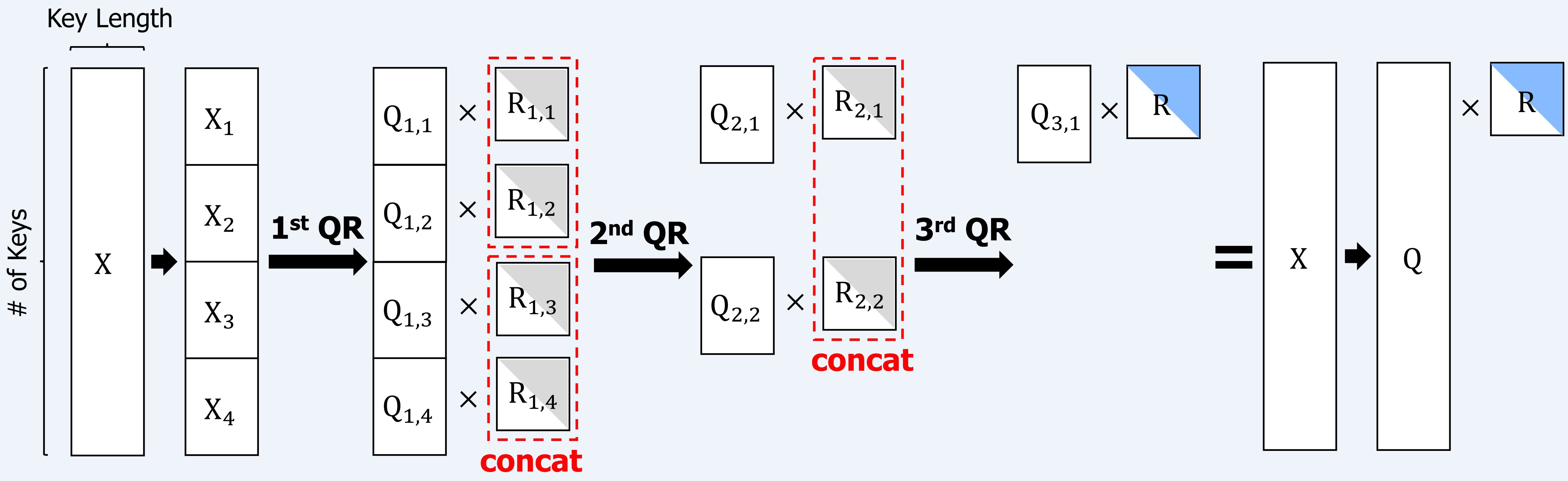
① **Algorithm** that reuses memoized intermediate results

② **Hardware** that offloads index training with FPGA accelerator



Insight from Parallel QR Decomposition

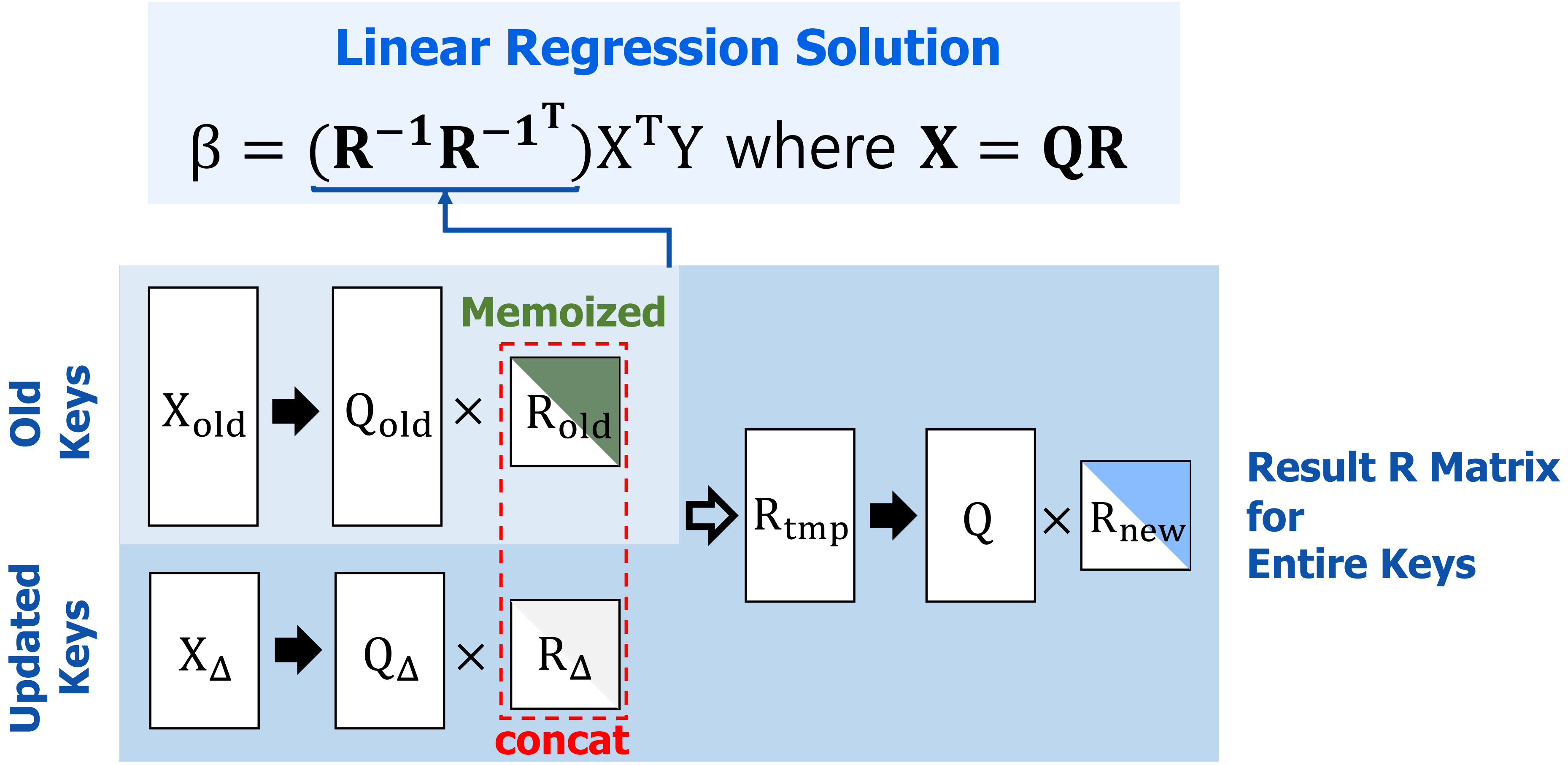
- Existing parallel QRD offers advantage to **tall-and-skinny** matrices
- Parallel QRD ensures **mathematical equivalence**



Algorithm Design

Incremental Index Learning

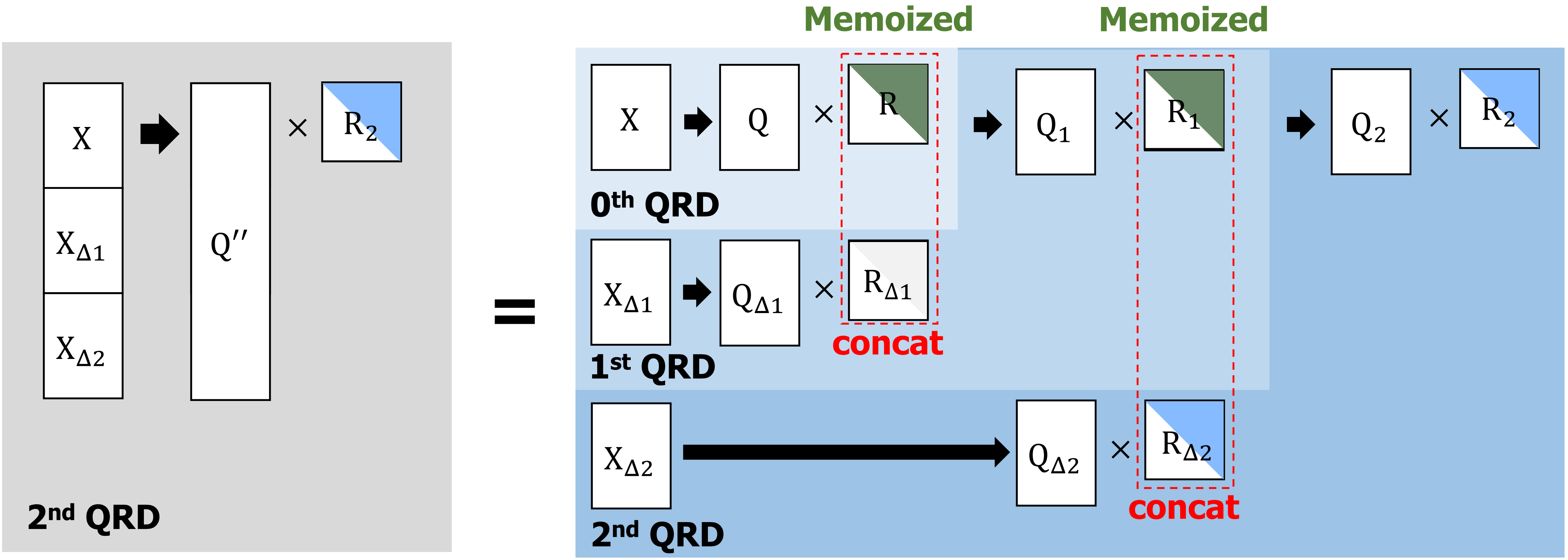
- Incremental index learning **reduces costly QRD** via memoization



Algorithm Design

Incremental Index Learning

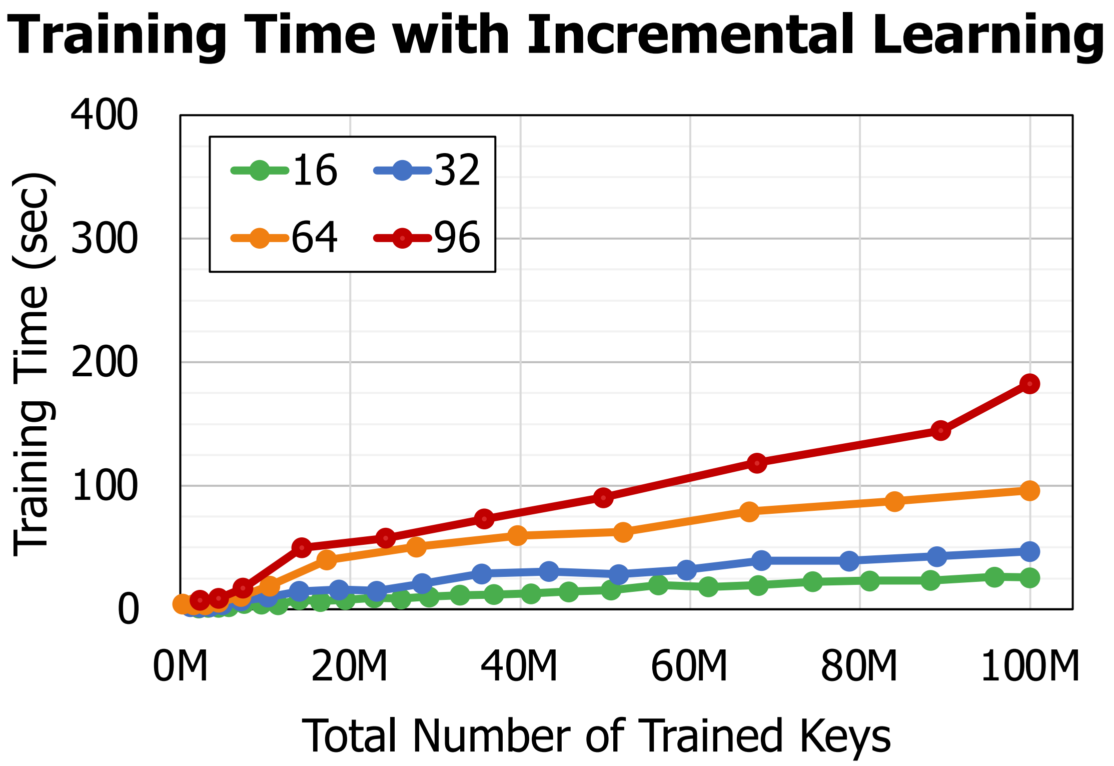
- There is no need to perform QRD for entire key matrix

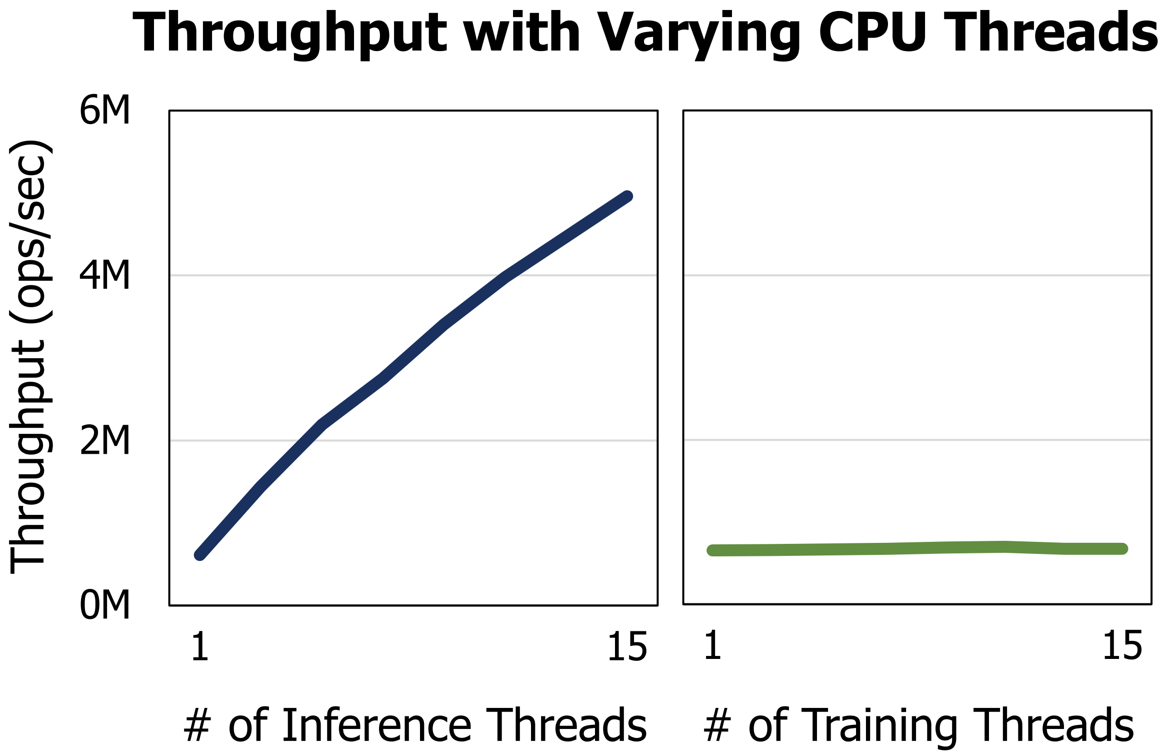


Naive QR Decomposition **Memoized QR Decomposition**

Why Do We Need Hardware Acceleration?

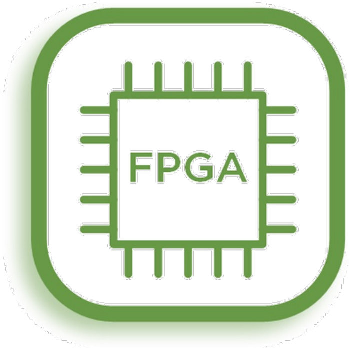
CPU-only solution is still slow due to **low efficiency in training**





Hardware Design

Hardware Selection: FPGA



Field Programmable Gate Array

- **Reconfigurable**
  Reprogrammable without changing hardware
- **Customizable**
  Programmable with user custom hardware logic
- **Parallelizable**
  Simultaneous operation of multiple logic blocks
- **Area & Energy Efficient**
  High performance at low operating cost

Hardware Design

FPGA Accelerator Architecture

Linear Regression Solution

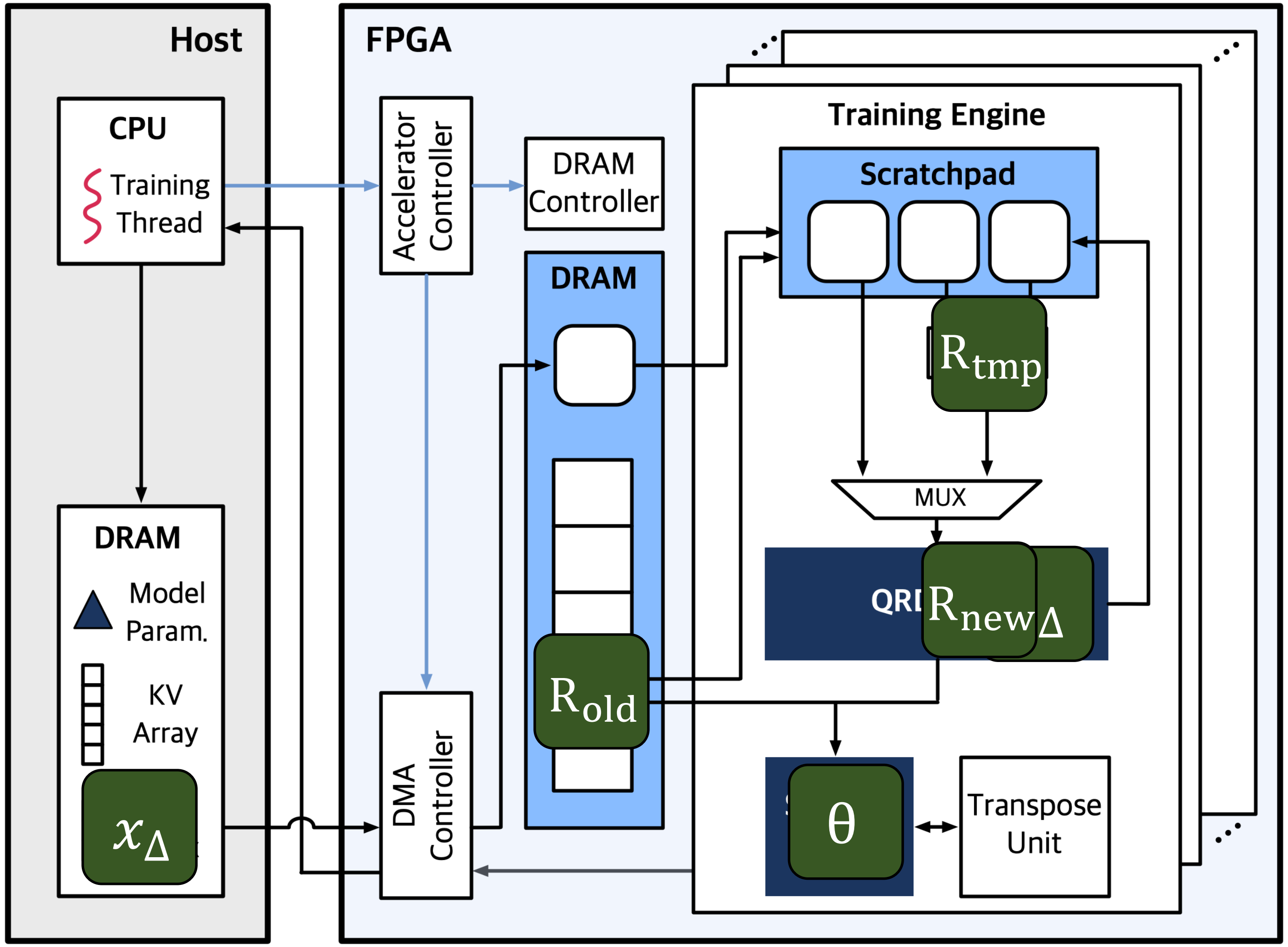
$\beta = (\mathbf{R}^{-1}\mathbf{R}^{-1^{\mathrm{T}}})\mathrm{X}^{\mathrm{T}}\mathrm{Y}$ where $\mathbf{X} = \mathbf{QR}$

FPGA accelerator calculates

$$\boldsymbol{\theta} = \left(\mathbf{R}^{-1}\mathbf{R}^{-1^{\mathrm{T}}}\right)$$

with incremental index learning

Calculation result is returned to host CPU



Evaluation Methodology

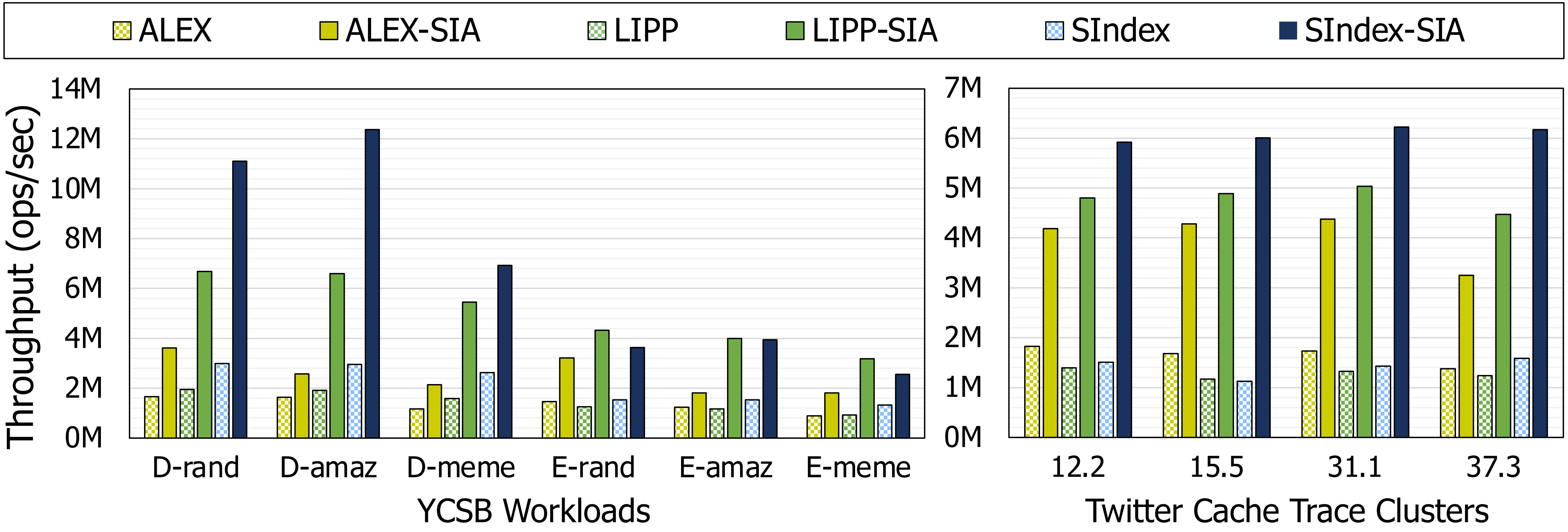
- **Baselines**
  - Wormhole[1]
  - Cuckoo Trie [1]
  - SIndex [2]
  - ALEX [2]
  - LIPP [2]

  [1] Traditional indexes
  [2] Updatable learned indexes

- **FPGA**
  - Intel Arria 10 GX-1150 (Synthesized to 272MHz)

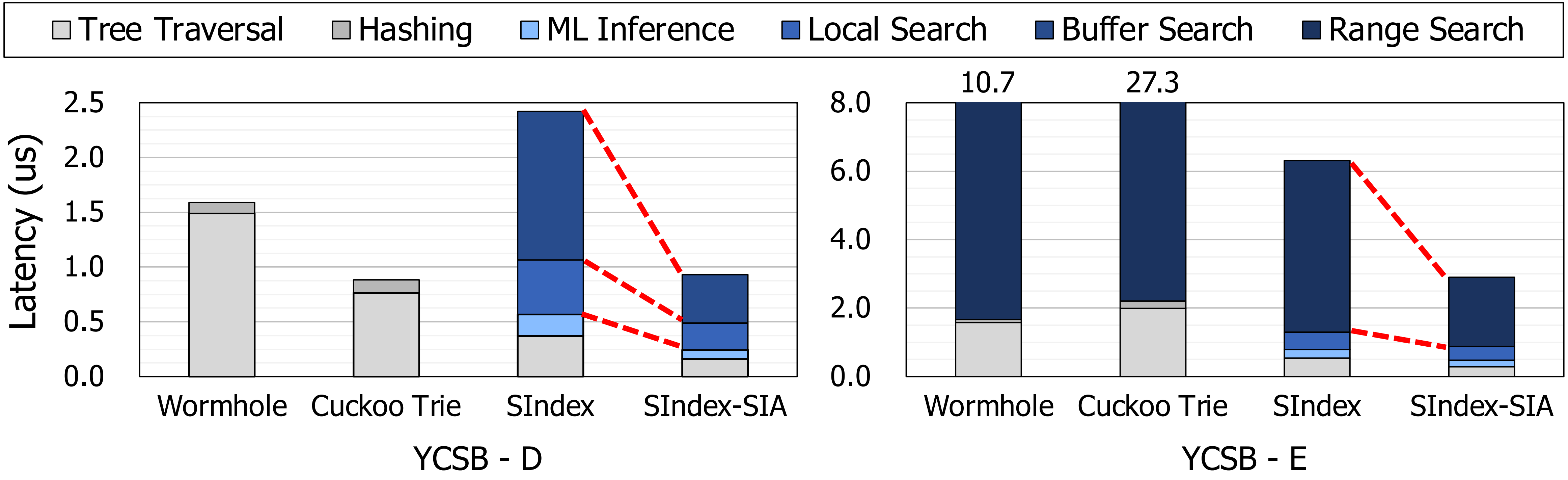
<table>
<tr><th>Dataset</th><th colspan="2">Workload</th></tr>
<tr><td>"amaz"
Amazon review dataset</td><td rowspan="3">YCSB – D
Read & Insert queries</td><td rowspan="3">YCSB – E
Range & Insert queries</td></tr>
<tr><td>"meme"
Memetracker dataset</td></tr>
<tr><td>"rand"
Randomly generated strings</td></tr>
<tr><td>Twitter Cache Trace
12.2, 15.5, 31.1, 37.3</td><td colspan="2">Twitter Cache Trace
12.2, 15.5, 31.1, 37.3
Read & Insert Queries</td></tr>
</table>

Performance Evaluation



Learned indexes with SIA shows an average of **2.9x throughput improvement** compared to learned indexes without SIA

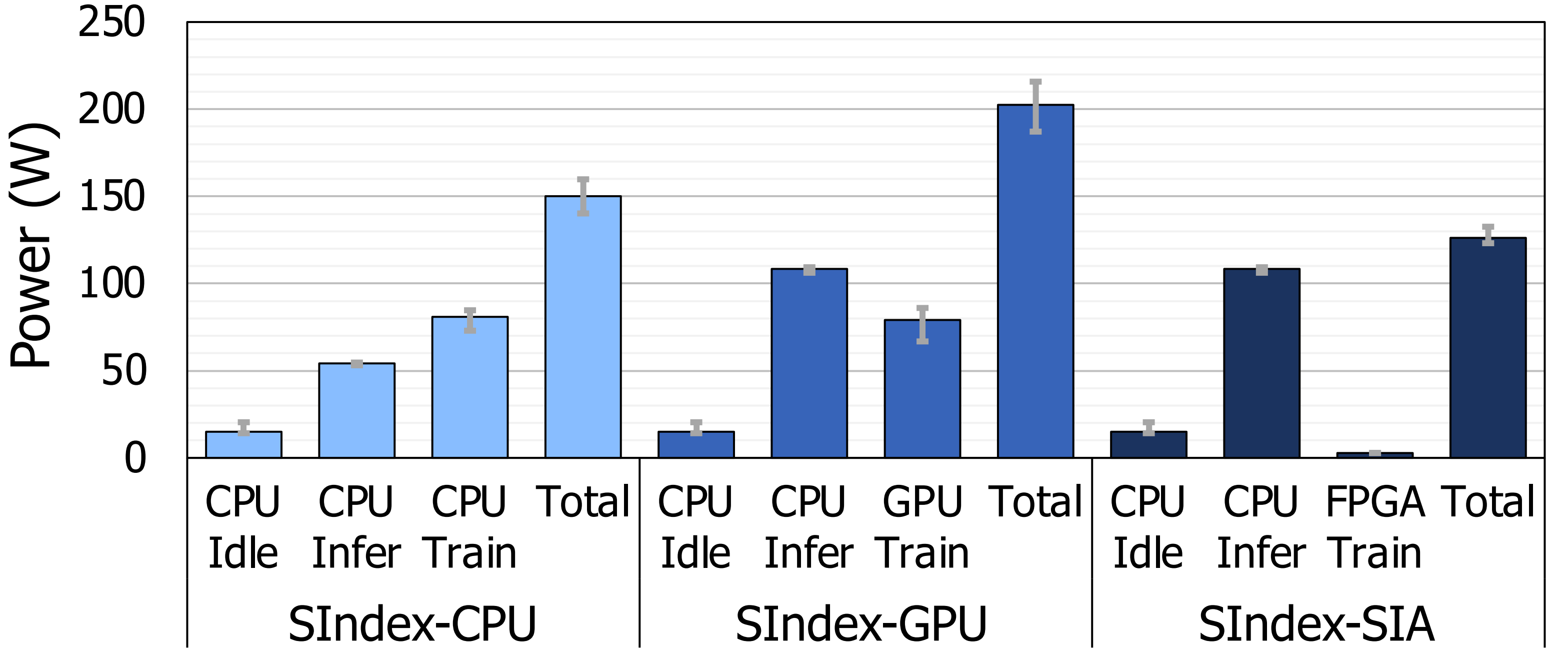
Latency Breakdown



Learned Index with SIA benefits from **reduced search time**

due to “freshness” of learning model

Energy Efficiency Evaluation



	Normalized Performance per Watt
SIndex-CPU	1.00x
SIndex-GPU	1.67x
SIndex-SIA	**2.89x**

* CPU: Intel Xeon Gold 6226R
* GPU: NVIDIA RTX 2080 TI

SIA achieves higher energy efficiency with **low energy usage of FPGA**

(**28x** less than NVIDIA RTX 2080 TI GPU)

Suitable for continuous retraining of **learned index system**

More Results in Paper

- **Hardware Resource Utilization**
- **Memory Consumption Comparison**
- **Ablation Study**
- **Throughput with Different Query Distribution**
- **Implication of Lazy Delete Query Handling**

Conclusion

- **SIA**
  - Algorithm-hardware co-designed string-key learned index system
- **Contributions**
  - Identifies and mitigates bottleneck of current learned index structures
  - Accelerates model retraining via memoization-based algorithmic approach
  - FPGA-based hardware design further reducing the training time
- **Results**
  - **2.9x** higher throughput than learned indexes without SIA