

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

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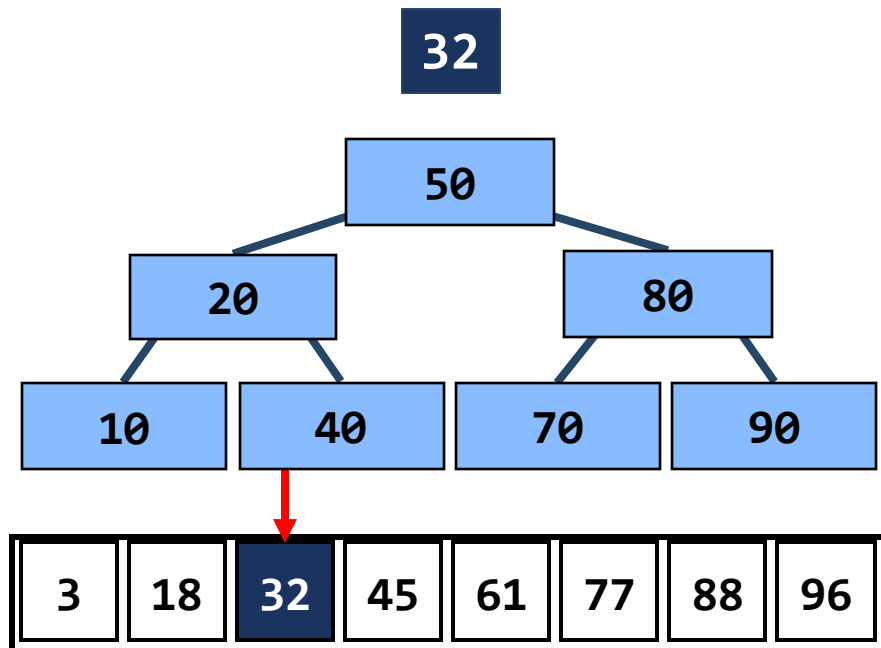
Georgia Institute of Technology[†]



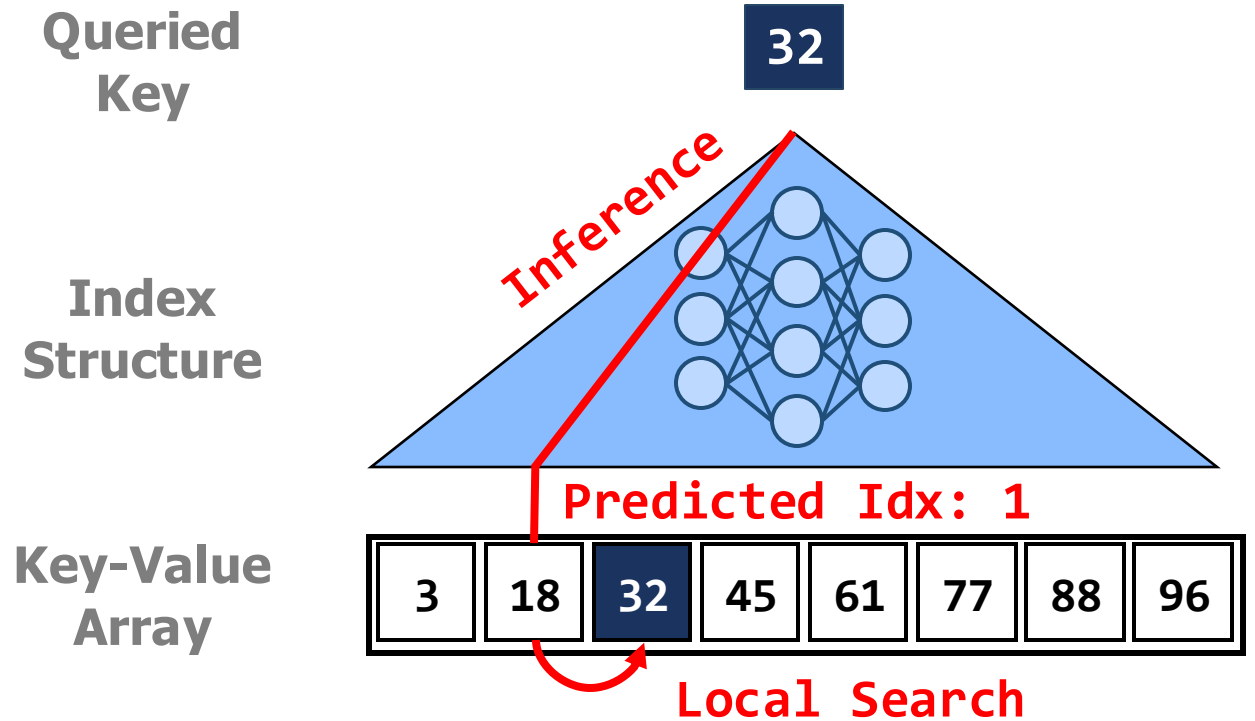
What is *learned index* anyway?

Learned Index Structure [1]

Traditional Index Structure



Learned Index Structure



[1] Kraska et al., The Case for Learned Index Structures, SIGMOD 2018

Learned Index Structure

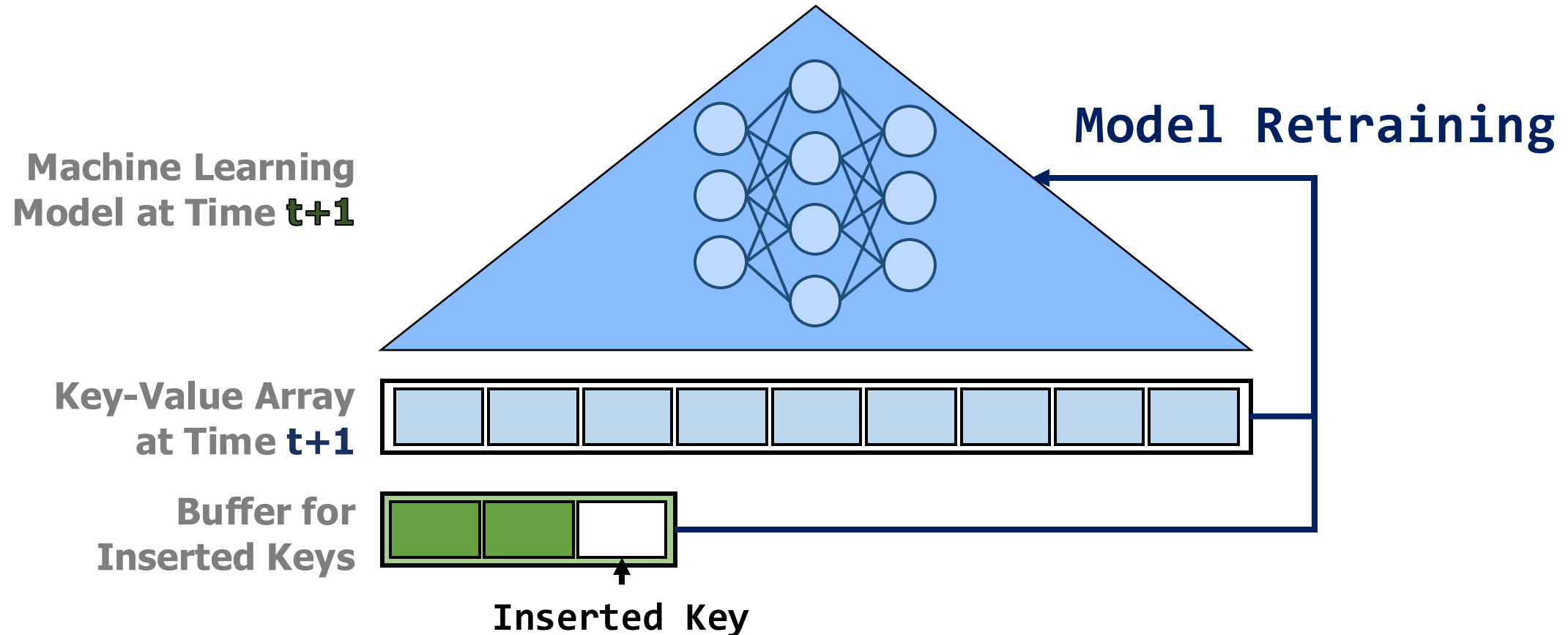
	Traditional Index	Learned Index
Time Complexity	▲	▼
Performance	▼	▲
Index Size	▲	▼

▪ Example Applications

- **Database:** BOURBON (OSDI 2020)
Learned Bigtable (ML for Systems at NeurIPS 2020)
- **DNA Sequencing:** BWA-MEME (Bioinformatics 2022)
BLESS (ISCA 2024)
- **Embedded Sensor:** Ding et al. (SENSORNETS 2023)



Updatable Learned Index [2, 3, 4]



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

[2] Ding et al., ALEX: An Updatable Adaptive Learned Index, SIGMOD 2020

[3] Tang et al., XIndex: A Scalable Learned Index for Multicore Data Storage, PPOPP 2020

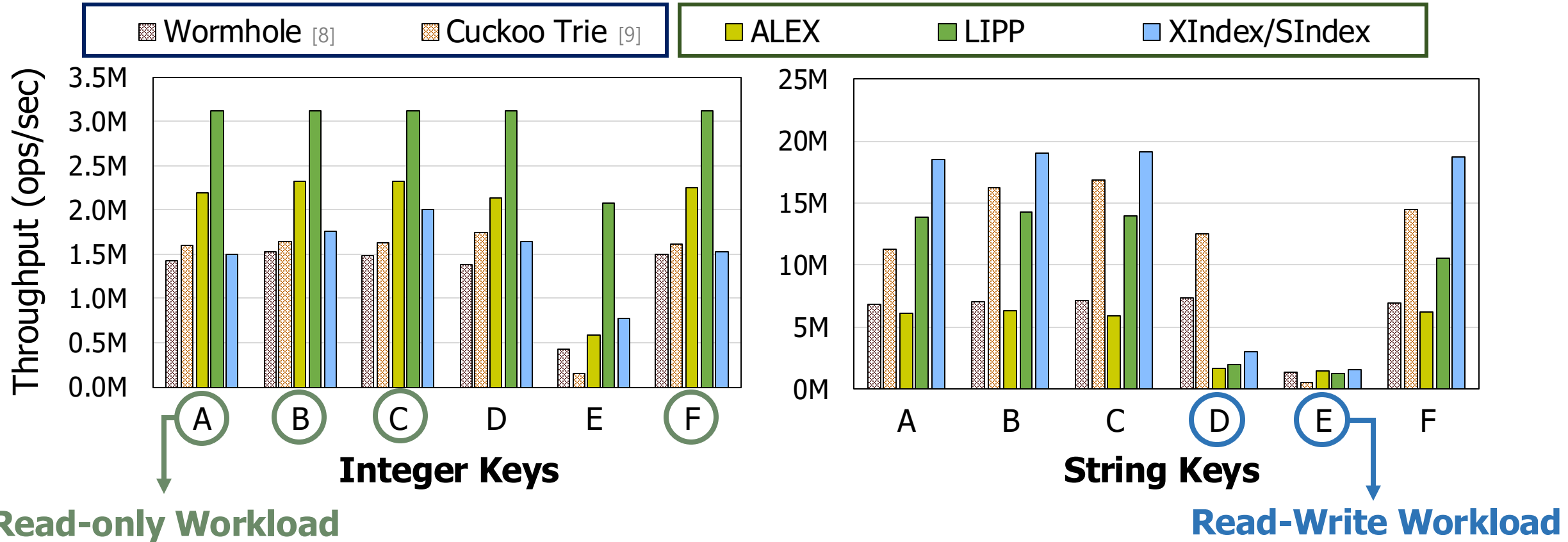
[4] Wang et al., SIndex: A Scalable Learned Index for String Keys, APSys 2020

Performance of Updatable Indexes

* Used YCSB (Yahoo Cloud Serving Benchmark) workloads

Non-Learned Indexes

Learned Indexes



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

[8] Wu et al., Wormhole: A Fast Ordered Index for In-memory Data Management, Eurosys 2019

[9] Zeitak et al., Cuckoo Trie: Exploiting Memory-Level Parallelism for Efficient DRAM Indexing, SOSP 2022

Importance of String-Keys



- String-key key-value store assists GenAI of Cisco by indexing 3,600+ documents [5]

[5] Omar Santos, Cisco Powers Secure, Responsible Artificial Intelligence Innovation at Scale with MongoDB, 2024



- Elasticsearch improves quality of GenAI model by 20% with the aid of string-key key-value store [6]

[6] LG CNS, Elasticsearch와 AI 검색 모델 통합으로 검색 정확도 고도화하다, 2024



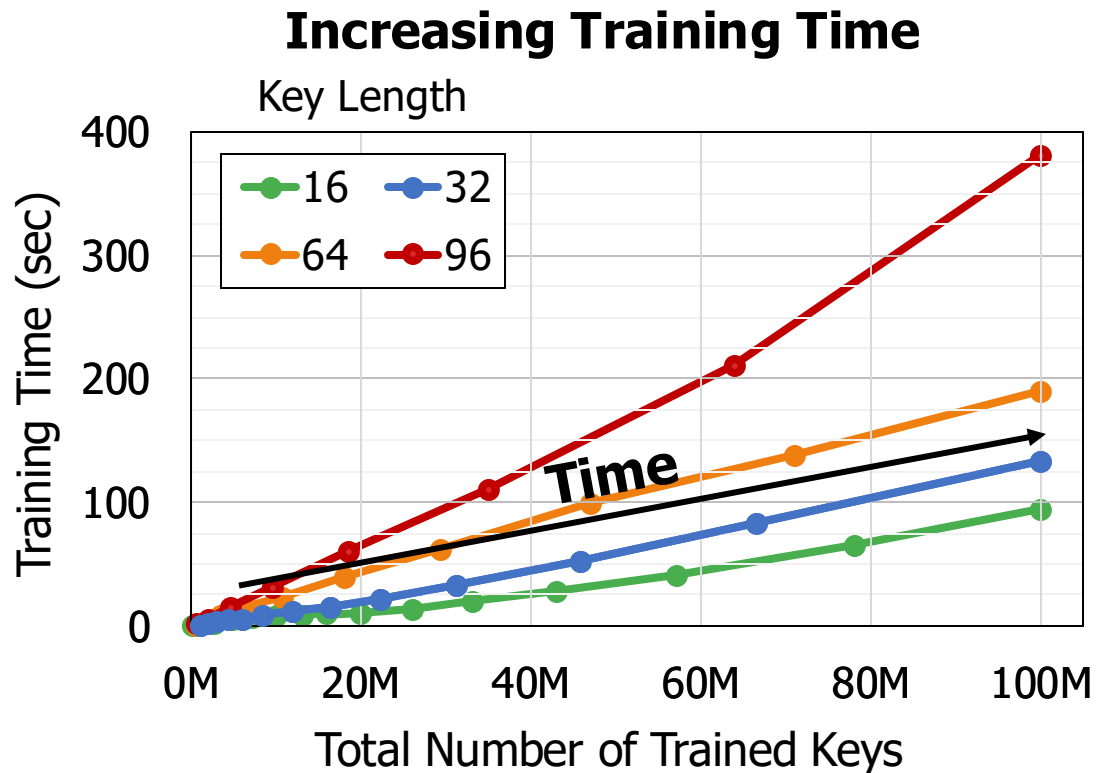
- Customer app should handle 10,000+ personalized requests per second for over 100 million items with under 40ms delay [7]

[7] Delivery Hero Helps Customers Navigate more than 100 Million Products with MongoDB Atlas Search, 2024

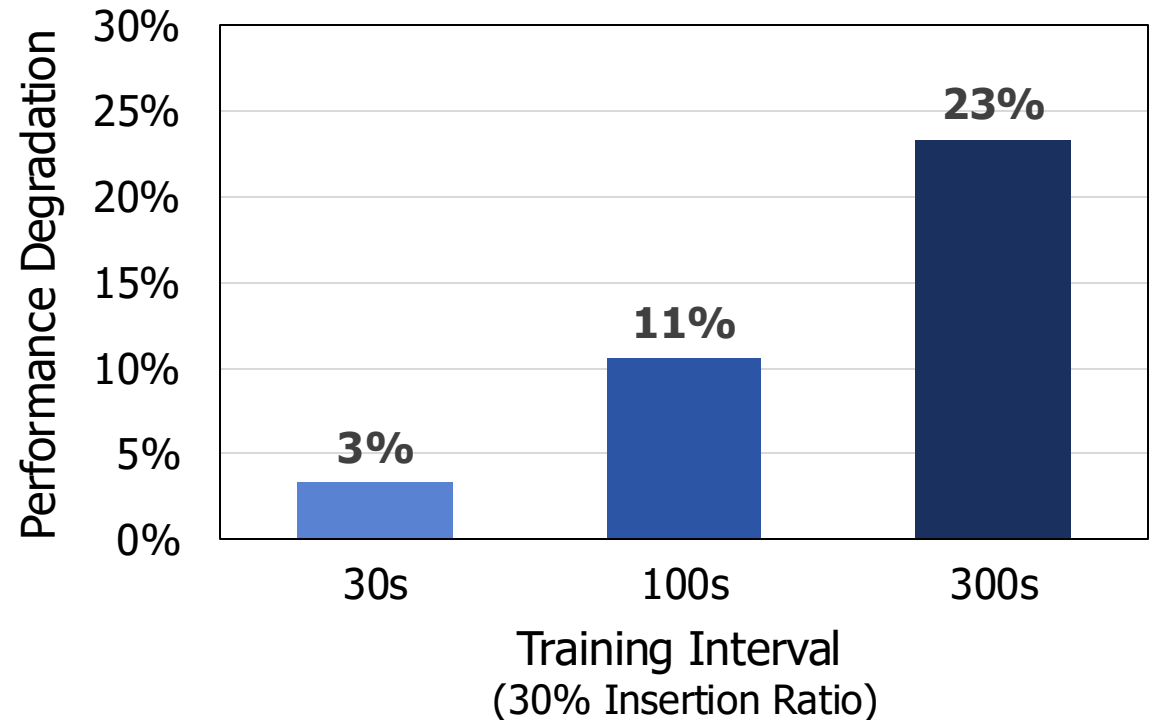
Bottlenecks of Learned Index Training

1. Bad scalability & performance due to accumulated keys

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



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**

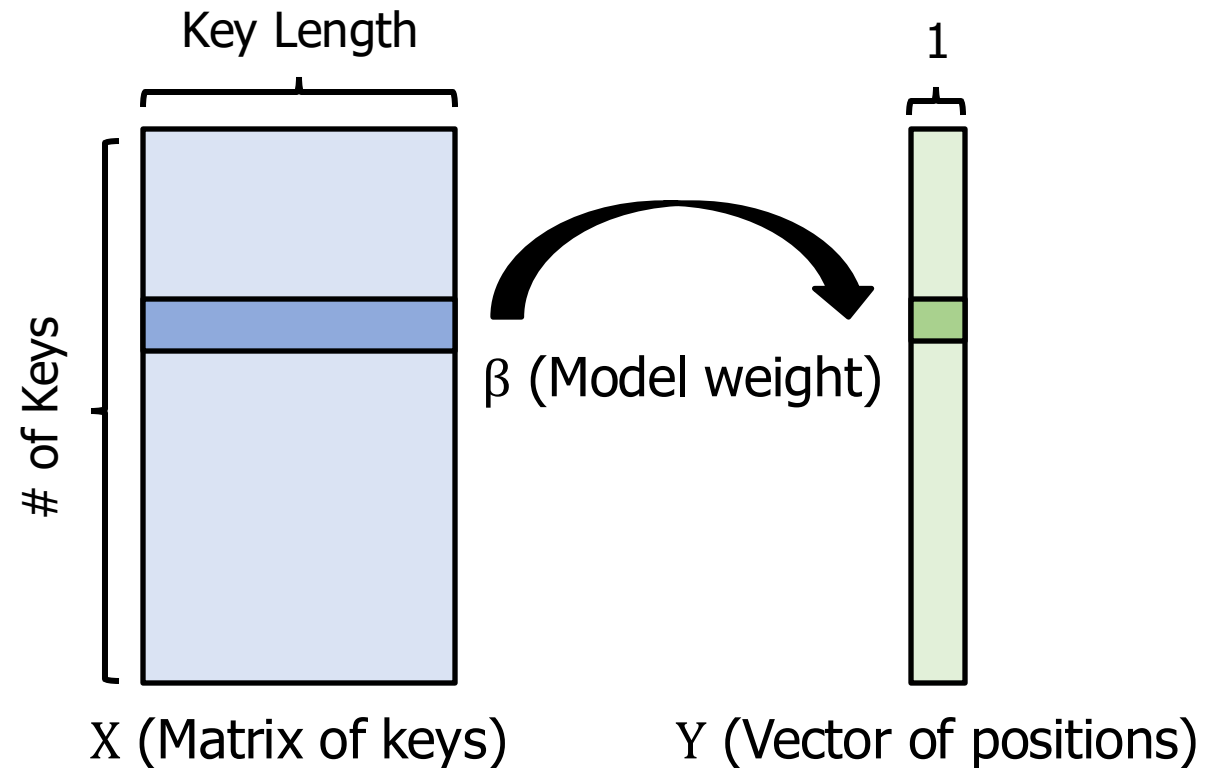
Linear Regression Model

$$X\beta = Y$$

Linear Regression Solution

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

, where $X = QR$



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

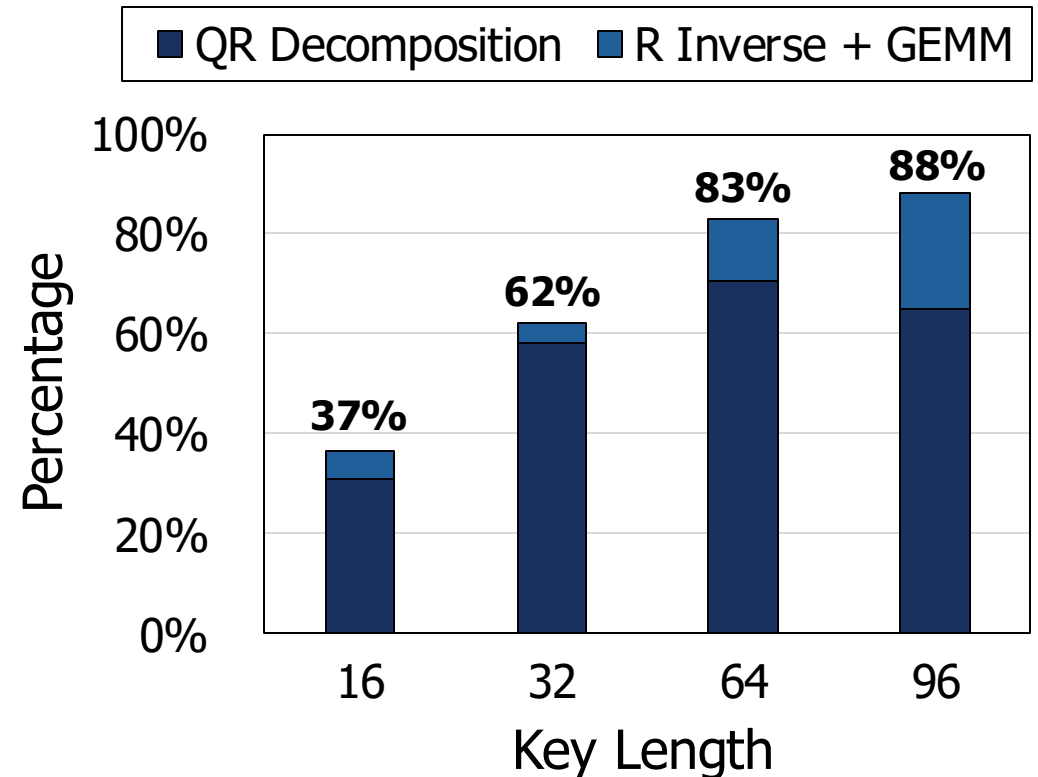
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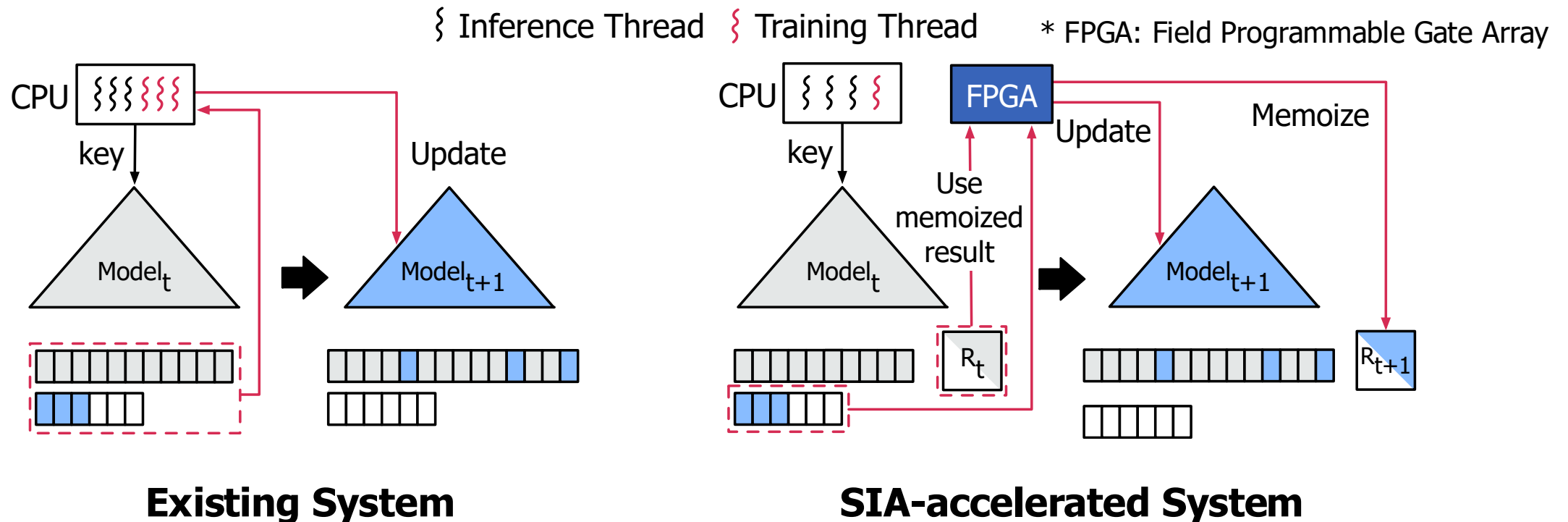


**Existing String-key Learned Index Systems
Offer Limited Performance**

SIA: System Overview

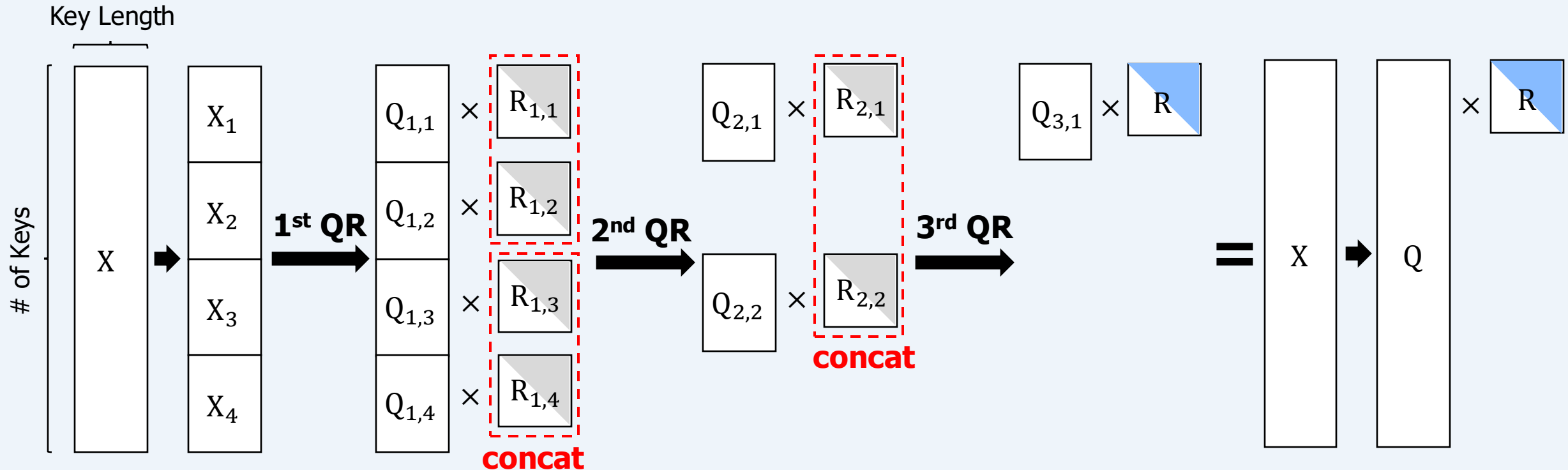
Algorithm-Hardware Co-designed String-key Learned Index System

- ① **Algorithm** that reuses memoized intermediate results
- ② **Hardware** that offloads index training with FPGA accelerator



Insight from Parallel QR Decomposition

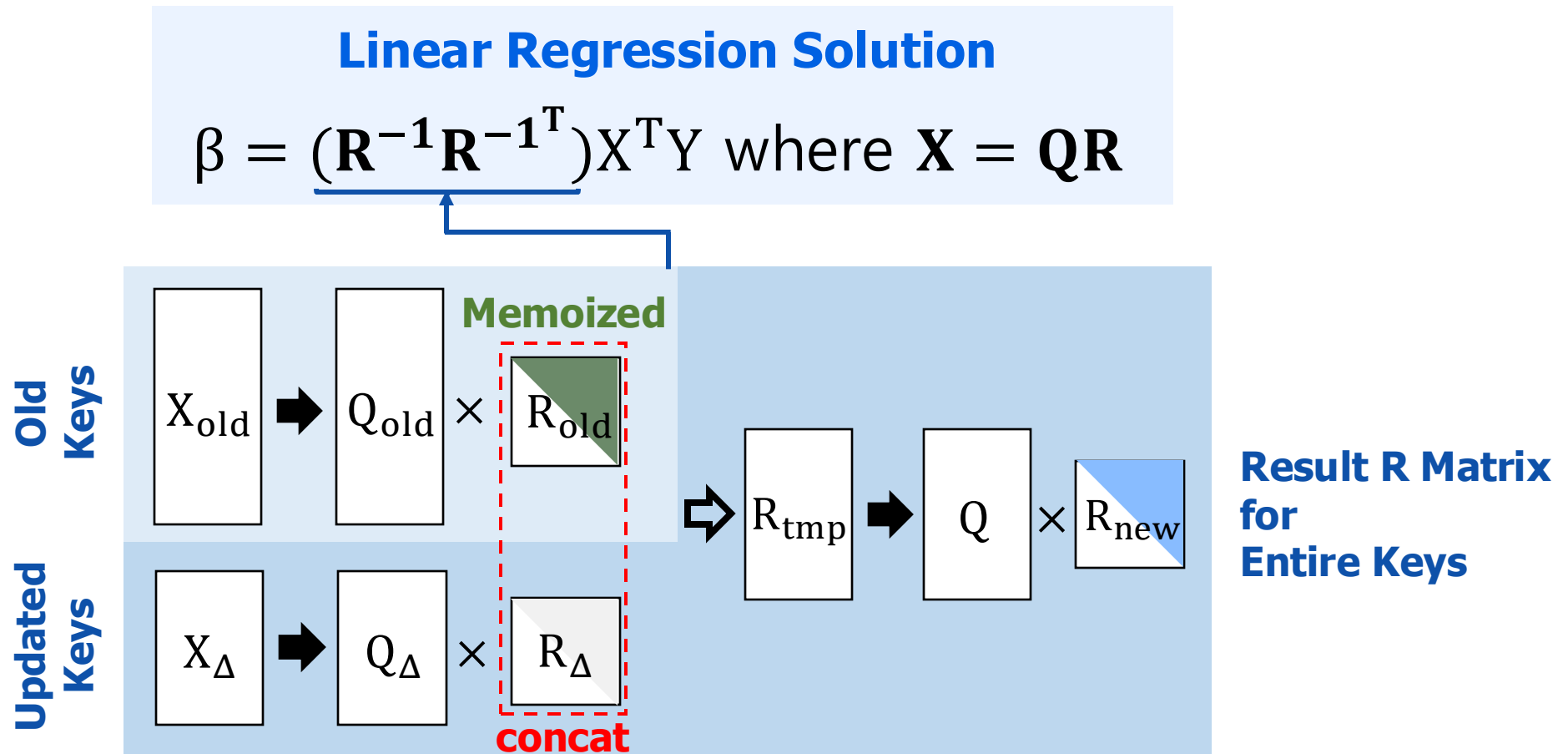
- Existing parallel QRD offers advantage to **tall-and-skinny** matrices
- Parallel QRD ensures **mathematical equivalence**



Algorithm Design

Incremental Index Learning

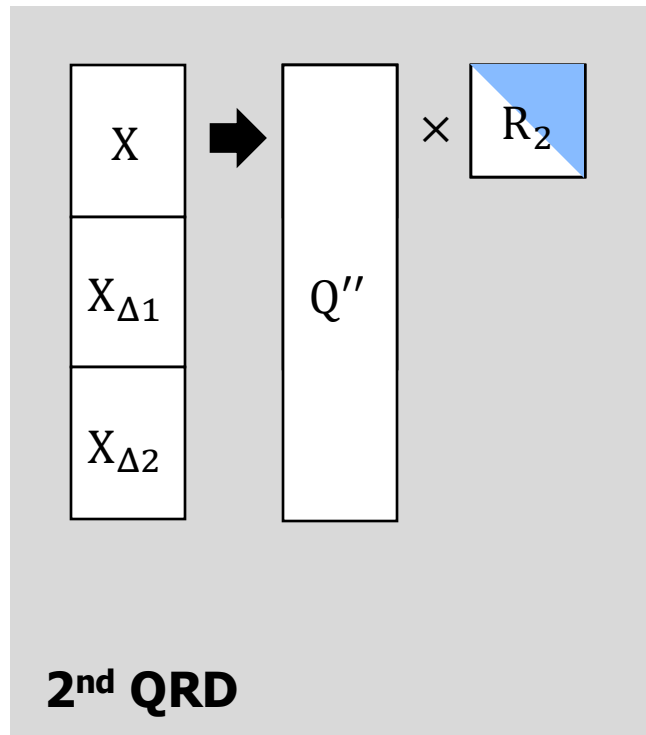
- Incremental index learning **reduces costly QRD** via memoization



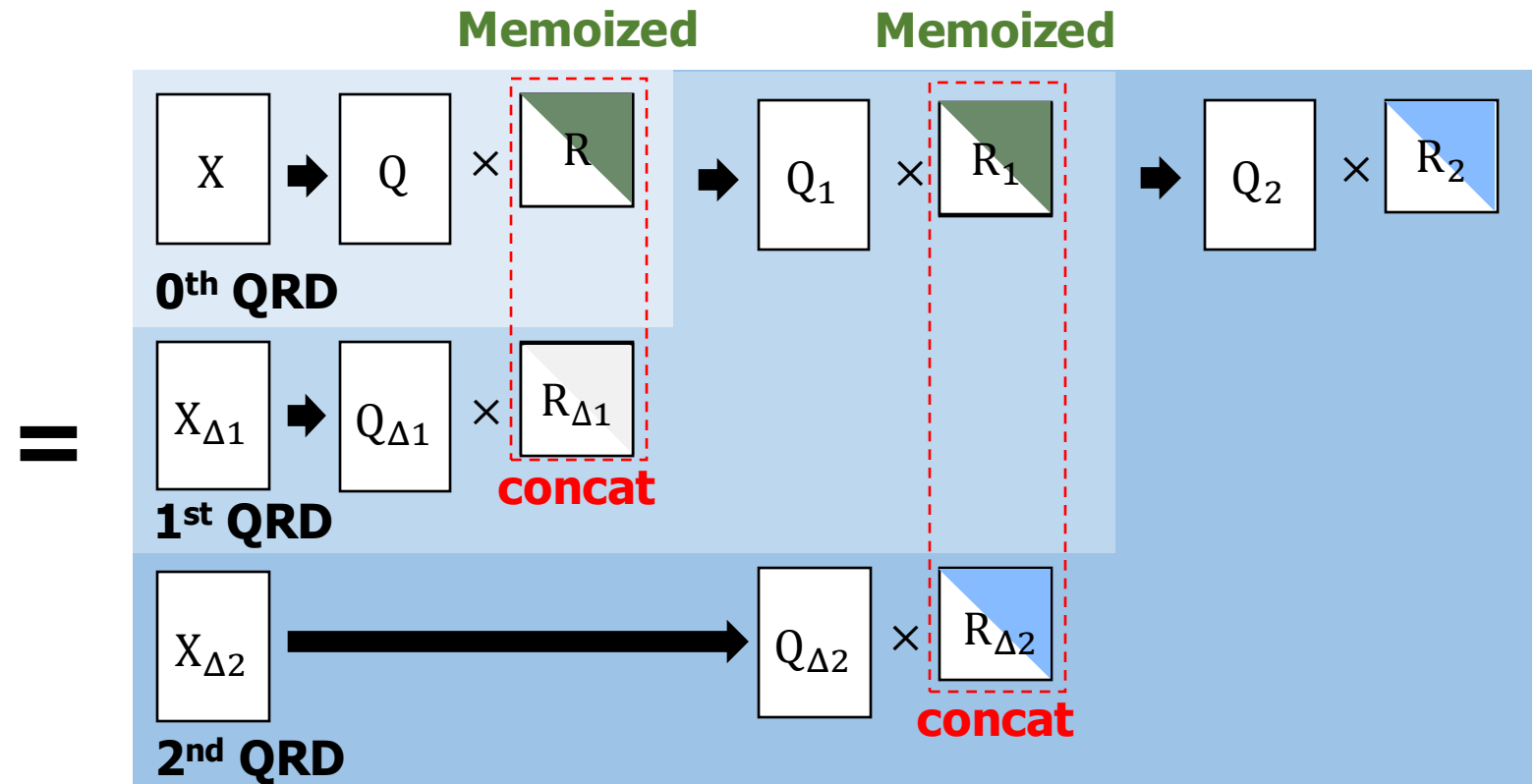
Algorithm Design

Incremental Index Learning

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



Naive QR Decomposition

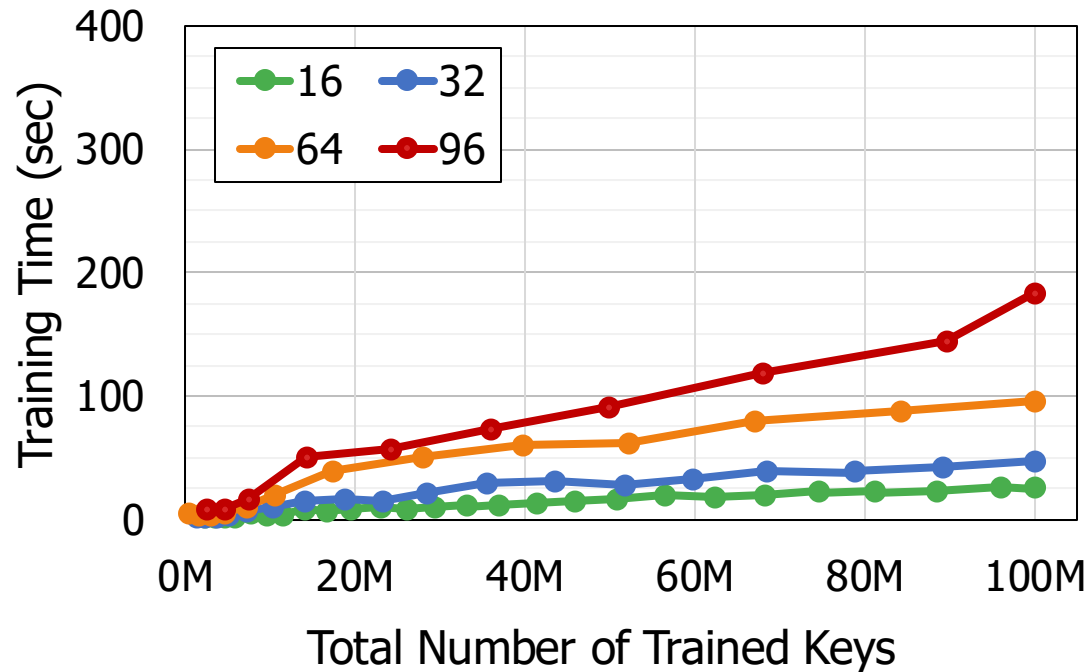


Memoized QR Decomposition

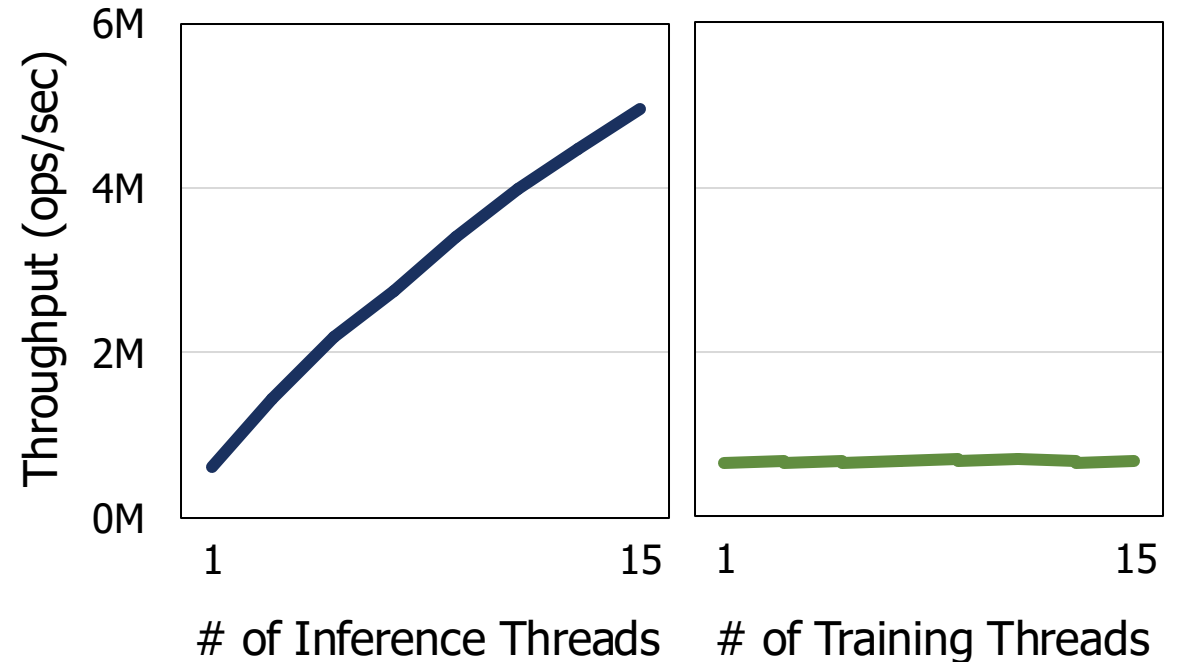
Why Do We Need Hardware Acceleration?

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

Training Time with Incremental Learning



Throughput with Varying CPU Threads



Hardware Design

Hardware Selection: FPGA



- **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

Field Programmable Gate Array

Hardware Design

FPGA Accelerator Architecture

Linear Regression Solution

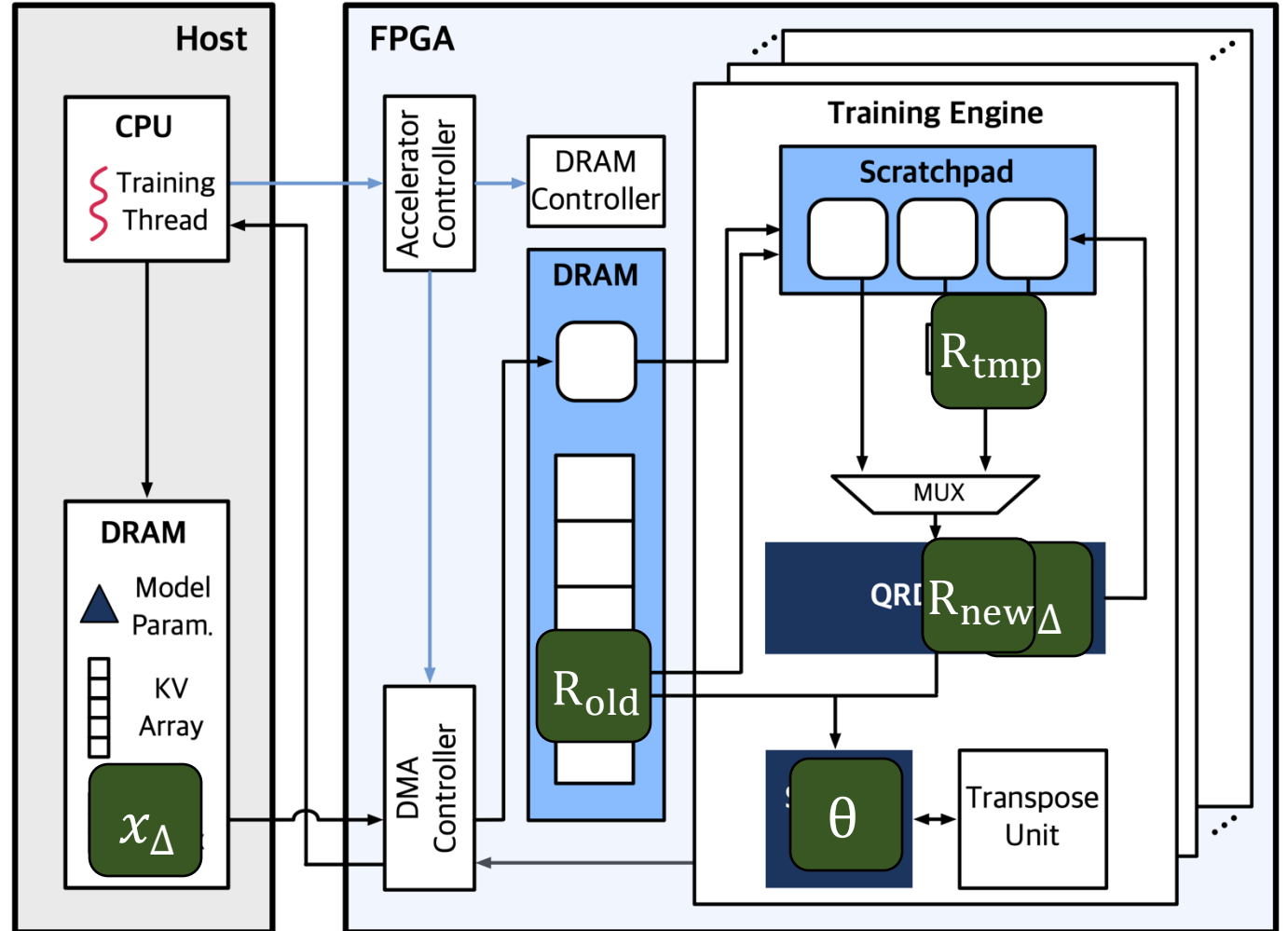
$$\beta = (\mathbf{R}^{-1}\mathbf{R}^{-1^T})\mathbf{X}^T\mathbf{Y} \text{ where } \mathbf{X} = \mathbf{QR}$$

FPGA accelerator calculates

$$\theta = (\mathbf{R}^{-1}\mathbf{R}^{-1^T})$$

with incremental index learning

Calculation result is returned to host CPU



Evaluation Methodology

▪ Baselines

- Wormhole^[*]
- Cuckoo Trie^[*]
- SIndex^[**]
- ALEX^[**]
- LIPP^[**]

[*] Non-learned indexes

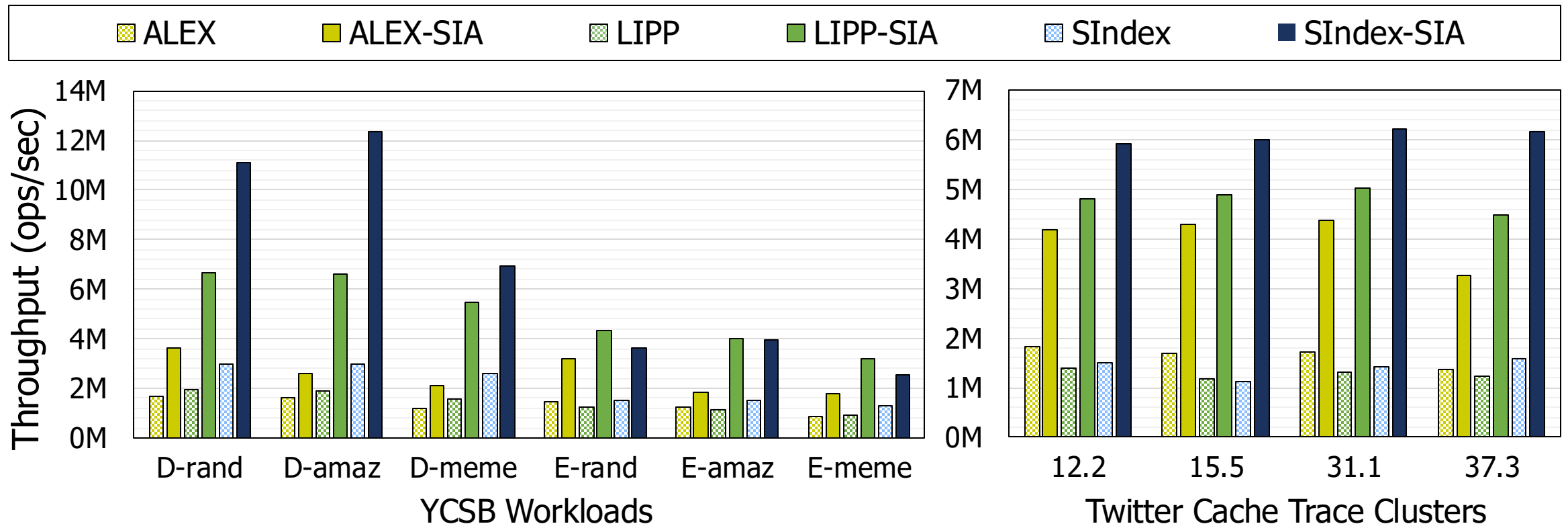
[**] Updatable learned indexes

▪ FPGA

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

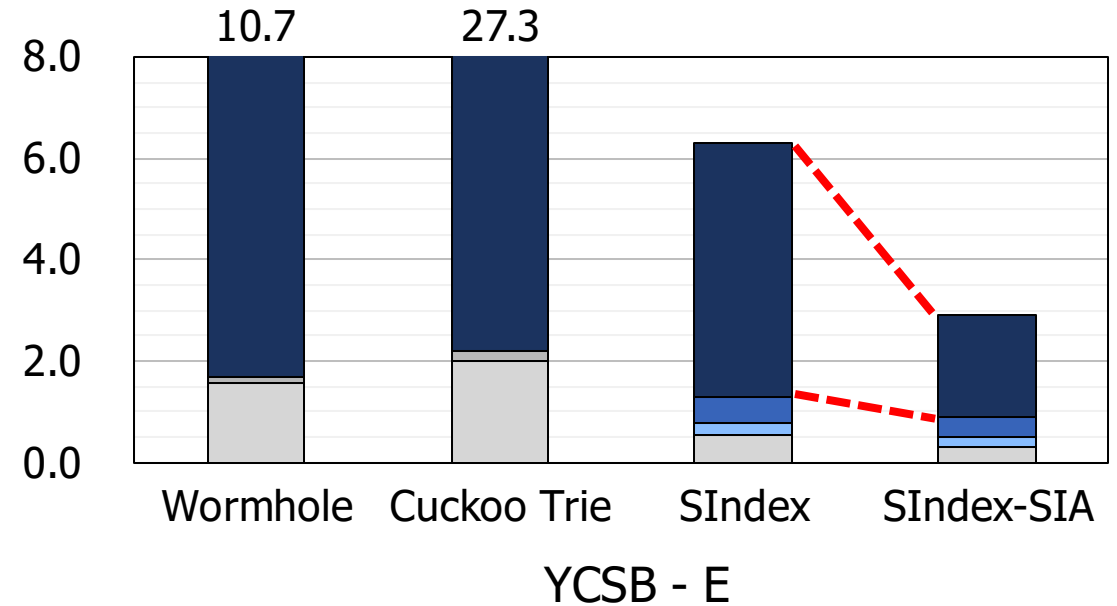
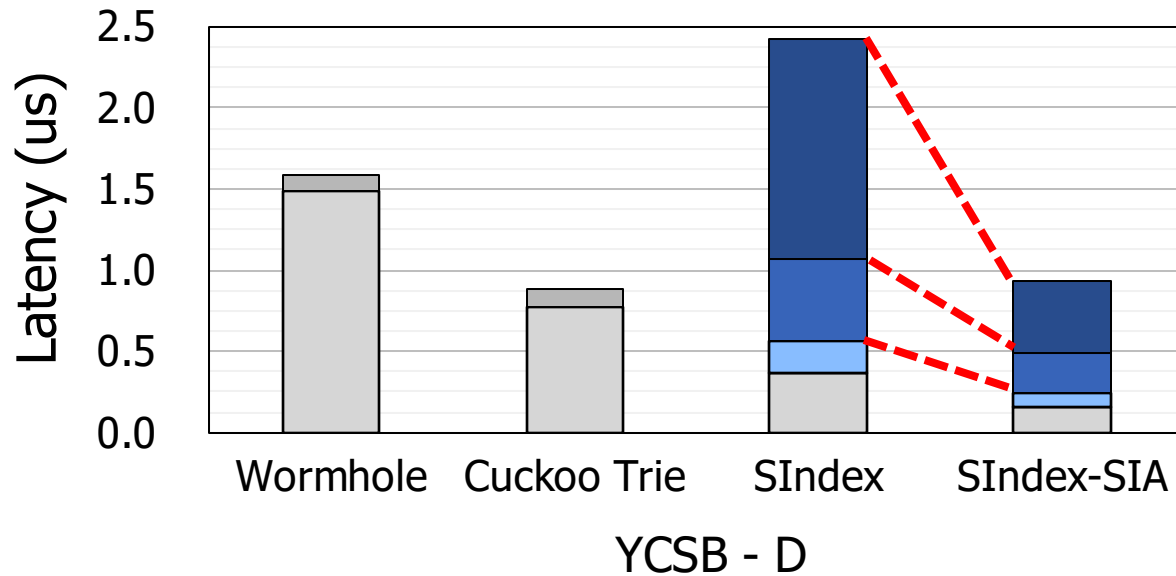
Dataset	Workload	
"amaz" Amazon review dataset	YCSB – D Read & Insert queries	YCSB – E Range & Insert queries
"meme" Memetracker dataset		
"rand" Randomly generated strings		
Twitter Cache Trace 12.2, 15.5, 31.1, 37.3	Twitter Cache Trace 12.2, 15.5, 31.1, 37.3 Read & Insert Queries	

Performance Evaluation



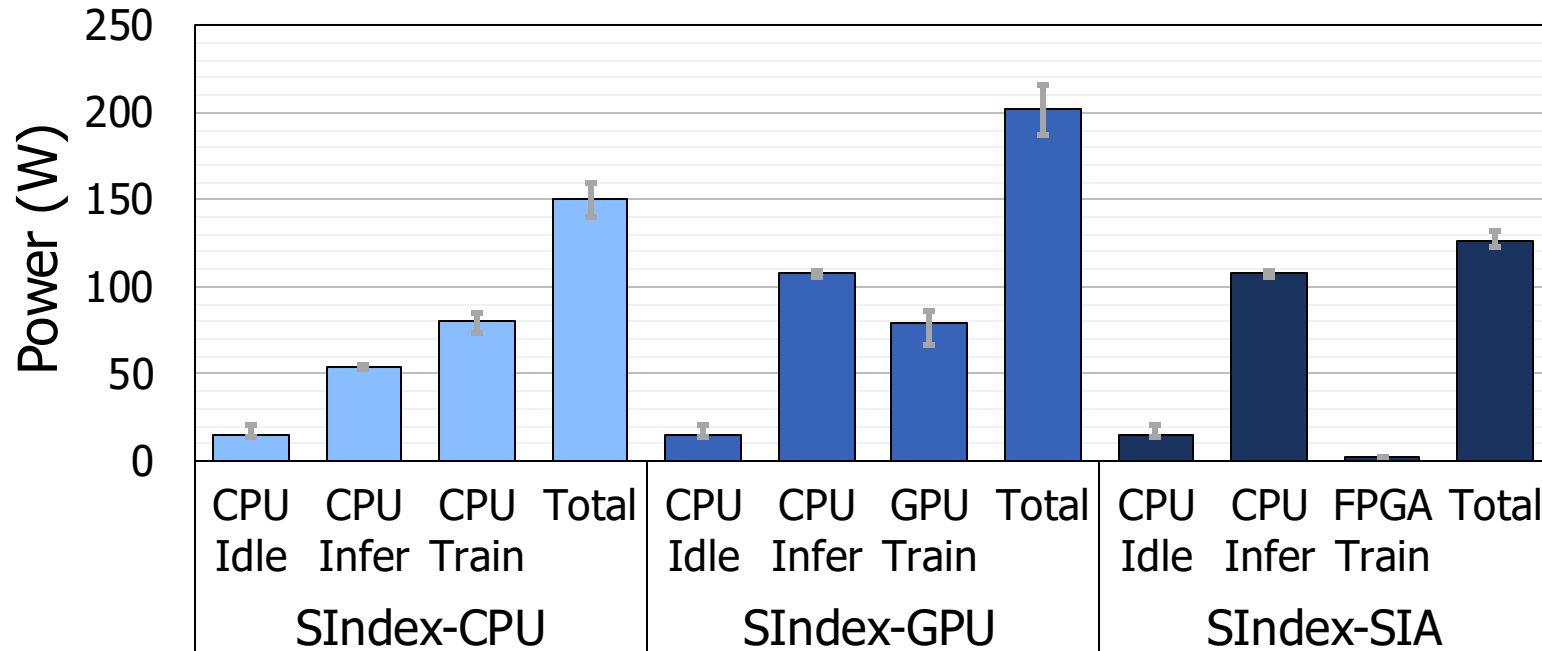
Learned indexes with SIA shows an average of **2.9x throughput improvement** compared to learned indexes without SIA

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**

- Fast and efficient

string-key learned index

through CPU-FPGA heterogeneous acceleration

- **Results**

- **2.9x** performance boost on existing string-key learned indexes

- **Work-in-Progress and Future Directions**

- Exploration of use cases for learned indexes in domain-specific applications
 - Vector DB for LLM (i.e., RAG)
 - Databases for ML training data