Can Learned Indexes be Built Efficiently? A Deep Dive into Sampling Trade-offs

Minguk Choi, Seehwan Yoo, Jongmoo Choi

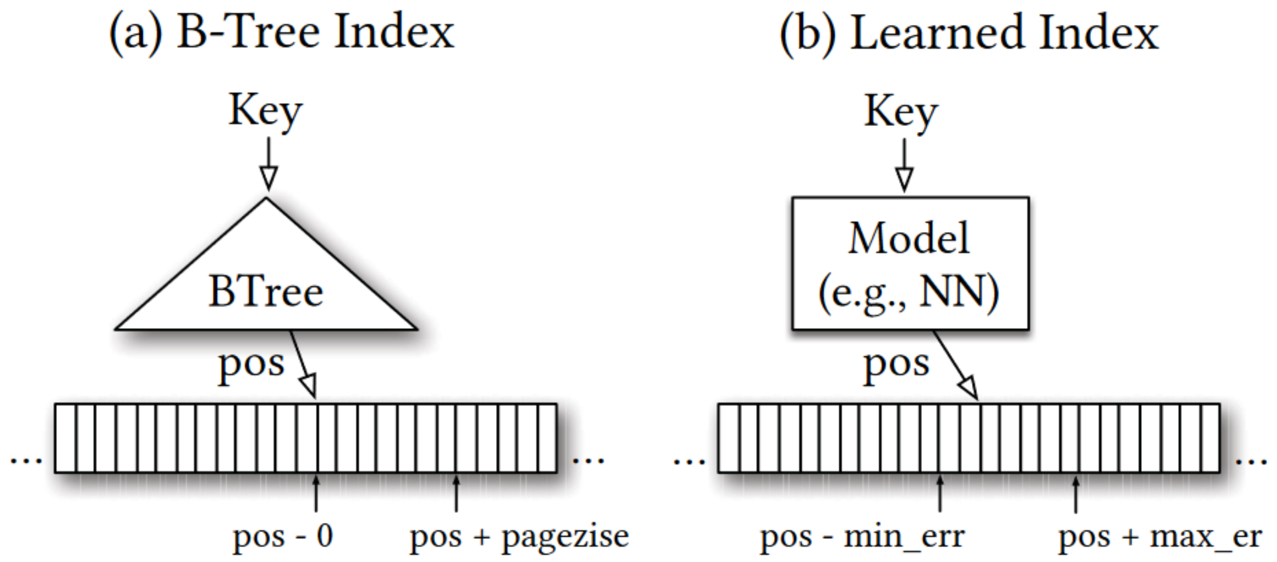
Dankook University, South Korea

Santiago Chile

SIGMOD PODS 2024

1. Introduction

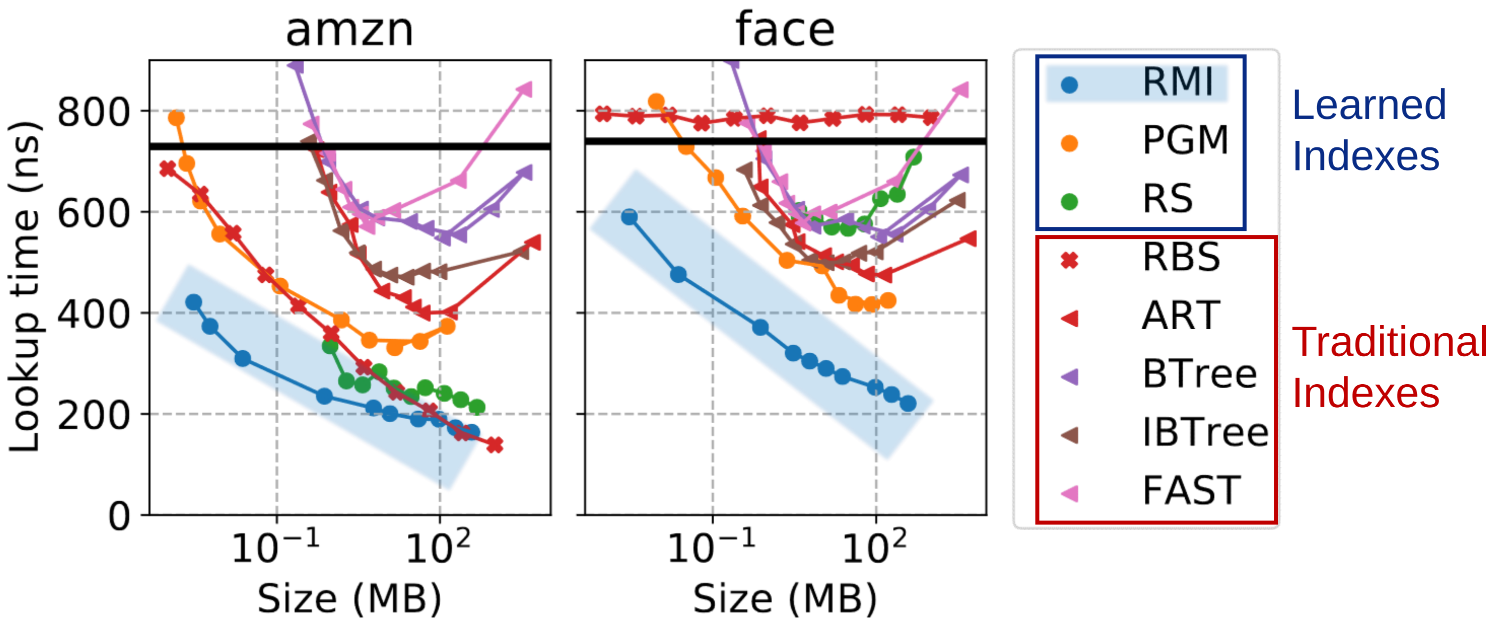
- Learned Index
  - Index structure employs machine learning techniques
  - View the index as a model that predicts the position of a key in a sorted array



(The Case for Learned Index Structures, SIGMOD '18)

1. Introduction

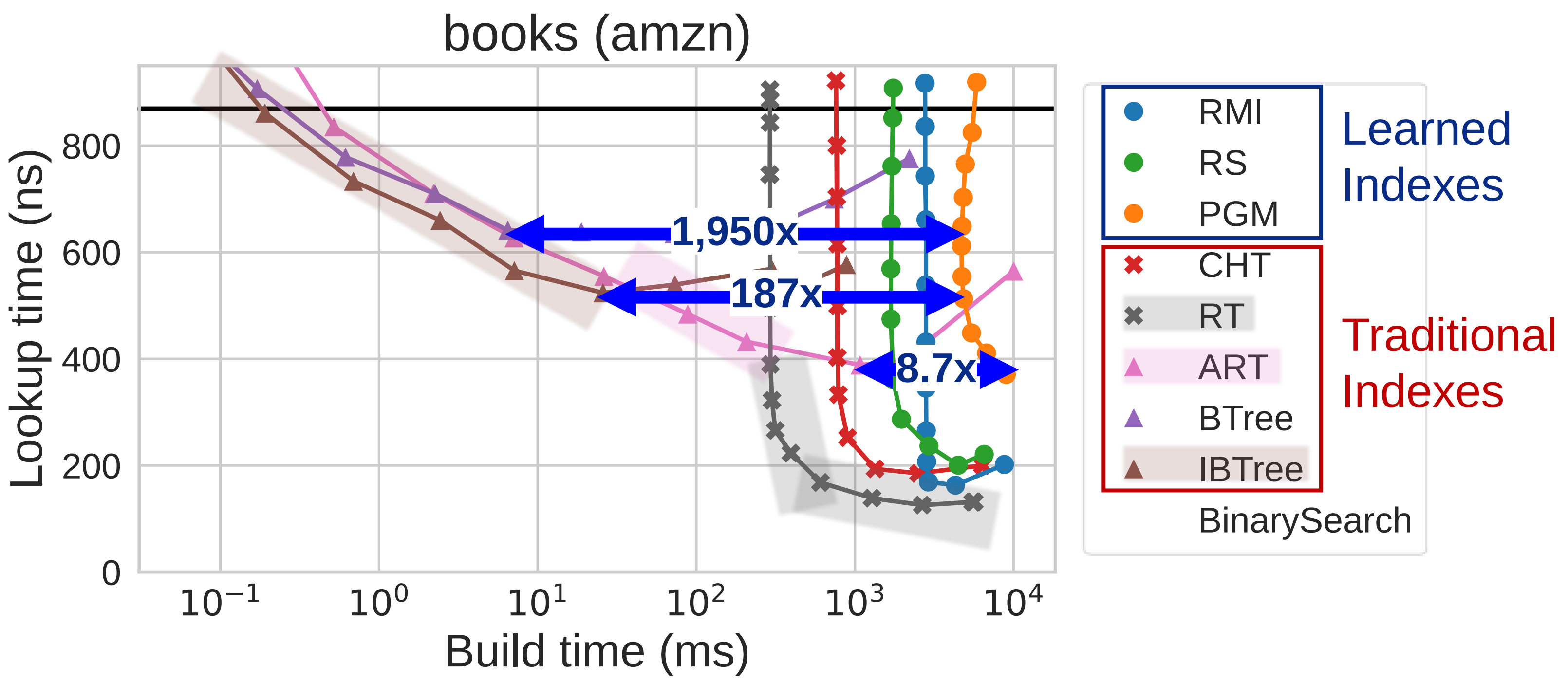
- Learned Index
  - Space-efficient by effectively compressing data distribution through the model
  - Pareto optimal in terms of index size and lookup latency in read-only workloads
    - No alternative that has both a smaller size and lower latency



(Benchmarking Learned Indexes, VLDB '20)

1. Introduction

- Limitation of Learned Index: **Long Index Build Time**
  - Significantly (up to about 2,000x) slower than traditional indexes
    - Not Pareto optimal (build-efficient) in terms of build time and lookup latency
  - Still, there are application (e.g., LSM-Tree) where the index build time is crucial

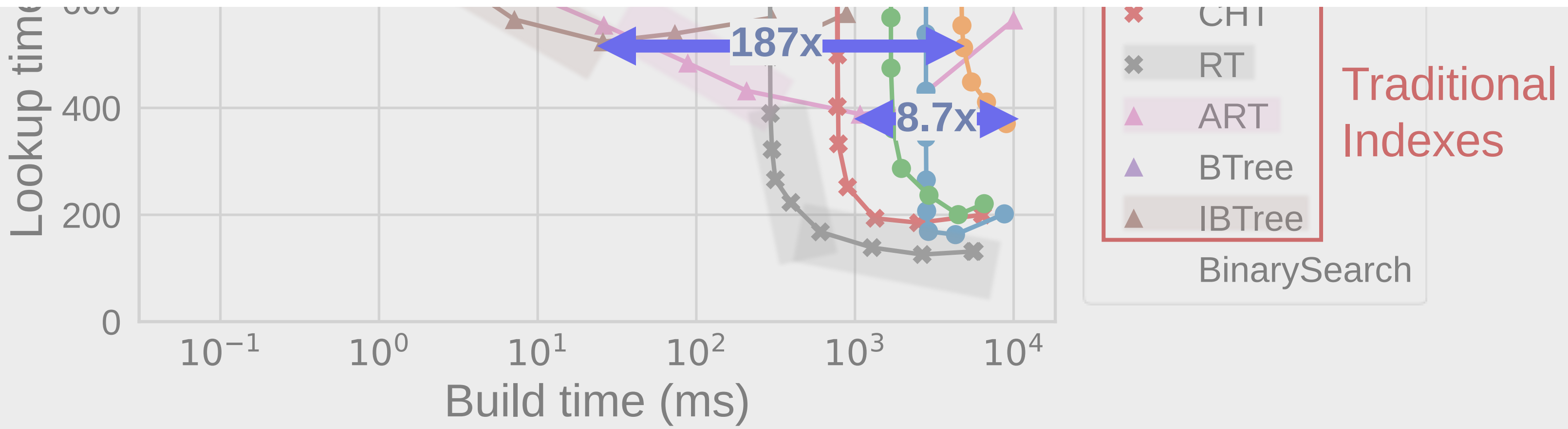


1. Introduction

- Limitation of Learned Index: **Long Index Build Time**
  - Significantly (up to about 2,000x) slower than traditional indexes

Long build time has been identified as
a high priority for future work in various papers:

RMI (SIGMOD `18), RadixSpline (aiDM `20), PGM-Index (VLDB `20), SOSD (VLDB `20), Critical-RMI (VLDB `22)



1. Introduction

- Primary Reason for Long Index Build Time

$$Index\ build\ time = Per - element\ overhead \times Number\ of\ elements$$

1) Higher per-element training overhead
2) Complete traversal and training

- To Mitigate Per-element Overhead
  - Light-weight training model: RadixSpline (aiDM `20), Bourbon (OSDI `20)
    - It still shows longer build time than traditional indexes

This study began with the question 🤔...

Since the learned index uses the model,

Can’t it learn efficiently even with less data?

1. Introduction

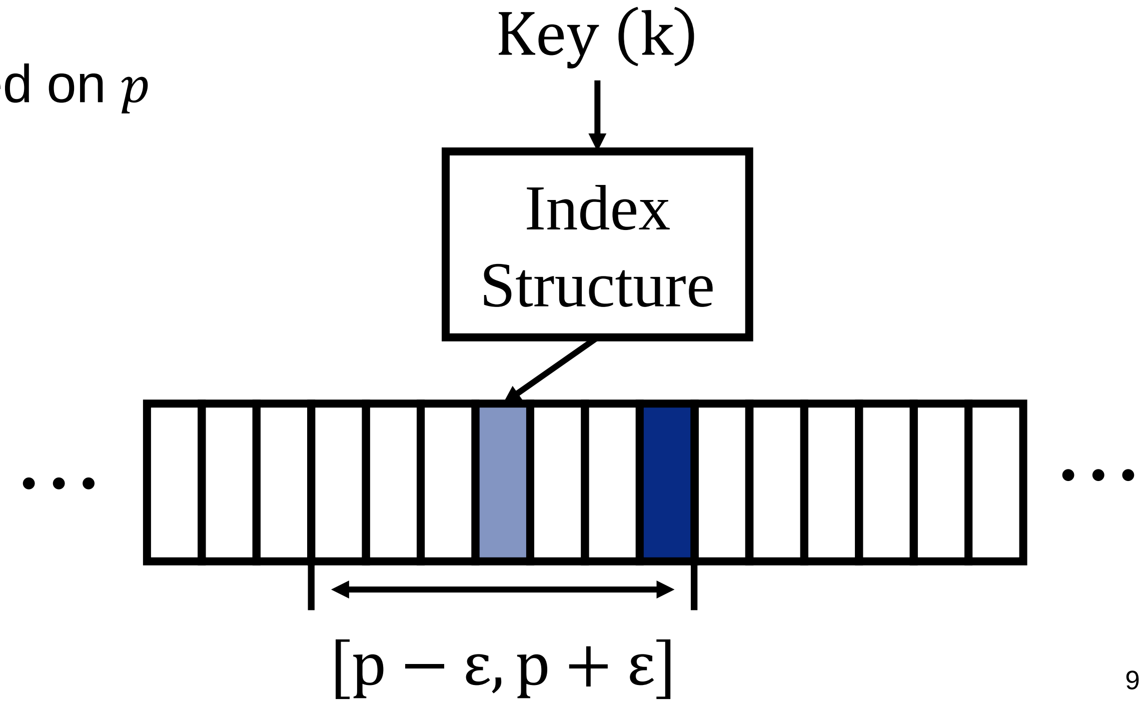
- Our Approach: **Sampling**
  - While sampling may seem simple and even naïve, it is indeed complex

- Challenges

  1. Absence of benchmark for sampling applied indexes
  2. Losing the error-bound property due to sampling loss
  3. Complex trade-offs in terms of model, index, and micro-architecture

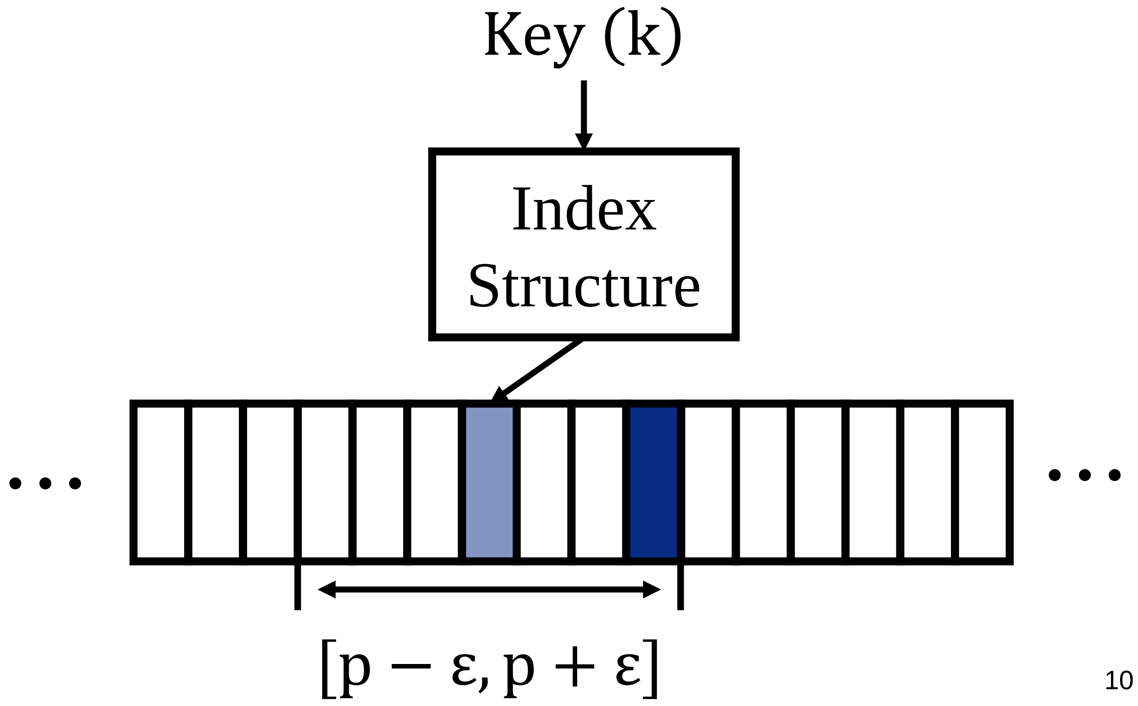
2. Background

- Workload: Read-only In-memory
  - Practical beginning point of learned index
  - Dataset (D): Sorted array of unique integer keys without duplicates
  - Lookup: Find the position of a lookup key k in D
    - ① Prediction: Estimate the position of k as p
    - ② Correction: Find the exact position of k based on p



2. Background

- Workload: Read-only In-memory
  - Error-bound property
    - $\forall\, k \in D,\ Error(k) = |Pred(k) - Pos(k)| \le \varepsilon\ (= error - bound)$
    - k exists in correction range $(= [p - \varepsilon, p + \varepsilon]) \rightarrow$ binary search
  - Important for robustness,
    - Especially where correction is expensive
    - E.g., Disk or remote I/O environments

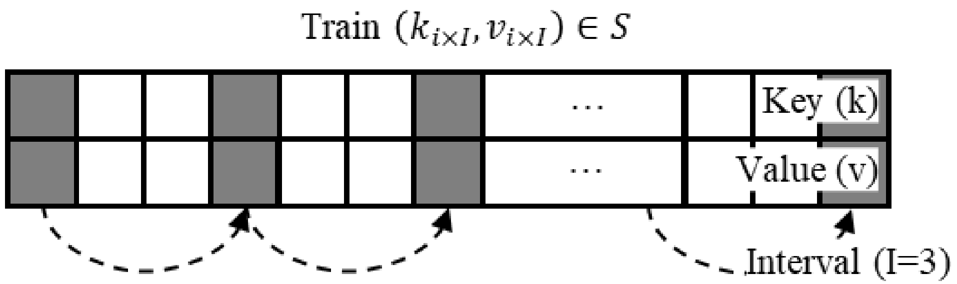


3. Design

1. Unified Sampling Algorithm & Implementation

BASIL (Benchmark of Sampling Applied Learned Indexes)

1) Unified sampling algorithm
   - Systematic sampling: extract every I^{th} (I = sampling interval) key from the first key to the last key
     - Pros: Simple, universal, no decision/reordering cost
     - Cons: Not optimal (other methods, e.g., adaptive, should be explored)
2) Unified sampling implementation
   - All indexes access and train only sample key-value data from the entire dataset



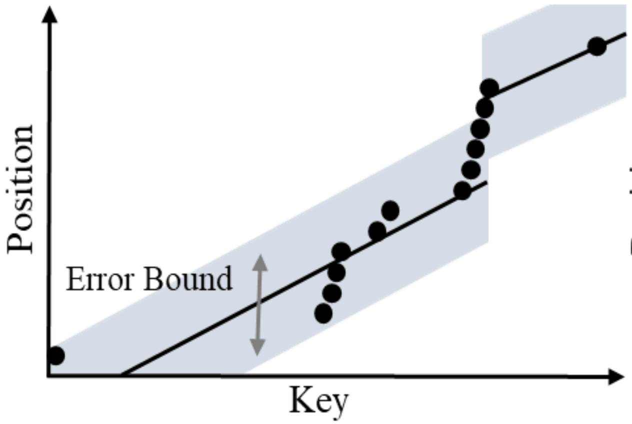
BASIL. Access I-th sample key-value in original dataset

3. Design

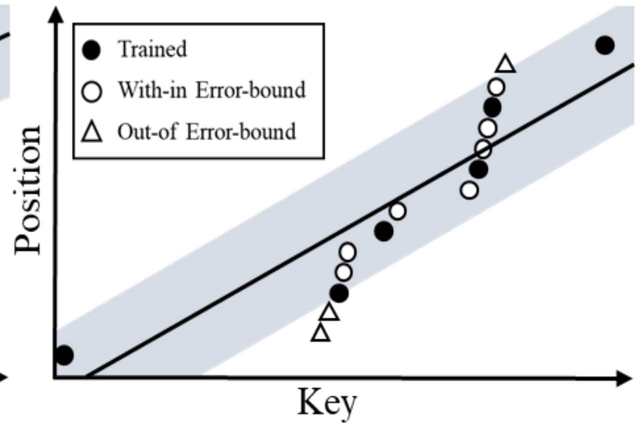
2. Sample Learning Algorithm

- EB-PLA (Error-bounded Piece-wise Linear Approximation)
  - Train all keys with error-bound $\varepsilon \rightarrow Error(k) \leq \varepsilon$
  - Train the sample I^{th} keys with error-bound $\varepsilon \nrightarrow Error(k) \leq \varepsilon$
    - ➢ Loss of the error-bound property, which is learning objective of the model

(a) Train All $(I = 1)$ with $\varepsilon = 3$



(b) Train Sample $(I = 3)$ with $\varepsilon = 3$



3. Design

2. Sample Learning Algorithm

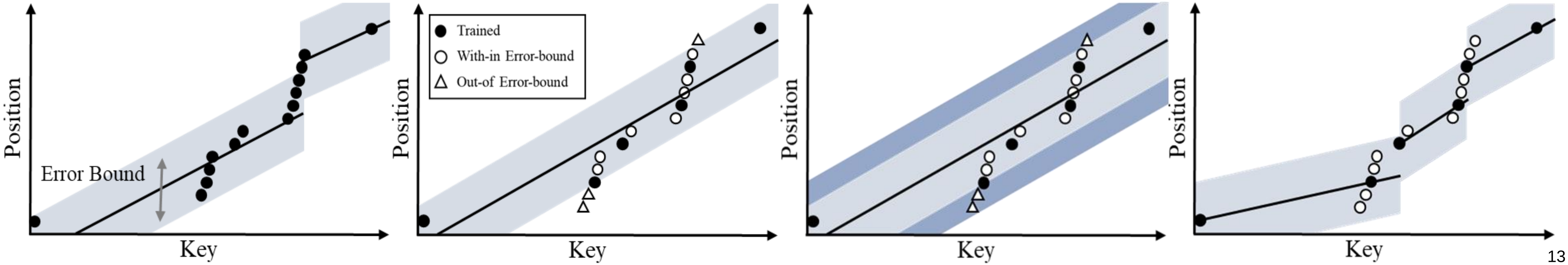
- Sample EB-PLA
  - Refine the error-bound due to sampling loss to $\varepsilon'(=\varepsilon+I-1) \rightarrow Error(k) \leq \varepsilon'$
    - ➢ Preserve the error-bound property, but cannot guarantee the desired error-bound (ε)
  - Replace the learning error-bound to $\delta(=\varepsilon-I+1) \rightarrow Error(k) \leq \varepsilon$
    - ➢ Preserve the error-bound (ε) by learning less data with a smaller and stricter error bound

(a) Train All (I = 1) with $\varepsilon = 3$

(b) Train Sample (I = 3) with $\varepsilon = 3$

(c) Refine the Error-bound ε from 3 to 5

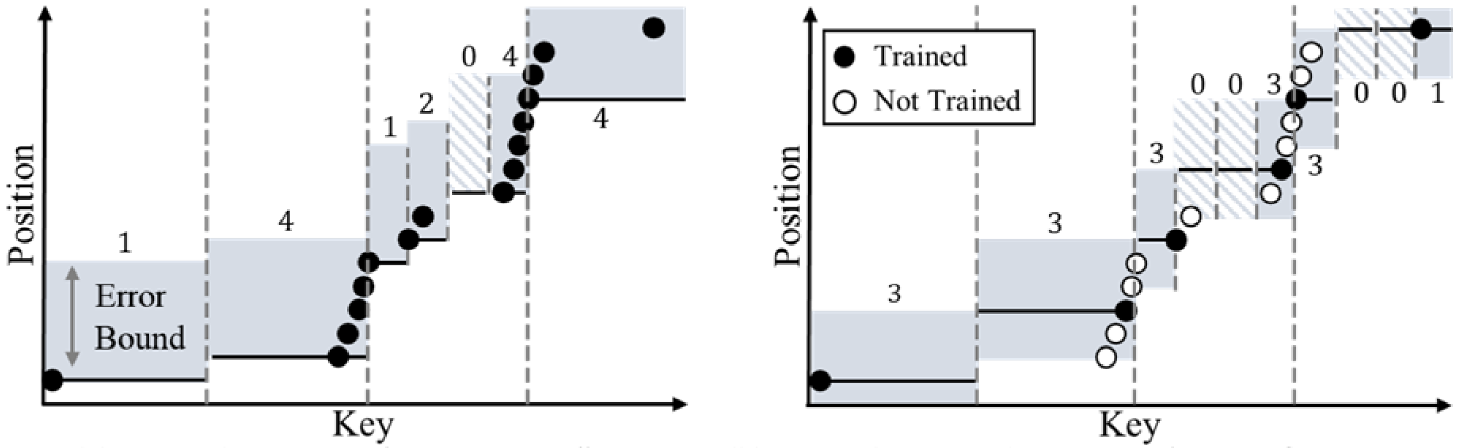
(d) Train Sample (I = 3) with $\delta = 1$



3. Design

2. Sample Learning Algorithm

- Sample EB-Histogram
  - Train all keys with the error-bound $\varepsilon \rightarrow k \in [p,\ p+\varepsilon]$
  - Train the sample I^{th} keys with smaller error-bound δ (=ε−I+1) $\rightarrow k \in [p-I+1,\ p+\delta]$
    - ➢ Preserve correction length $(\varepsilon + 1 = \delta + I)$

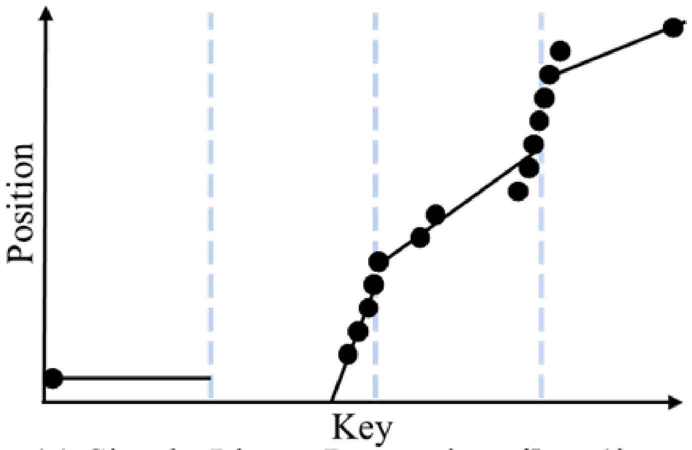


(a) EB-Histogram (I = 1, ε = 5) (b) Sample EB-Histogram (I = 1, δ = 3, ε = 5)

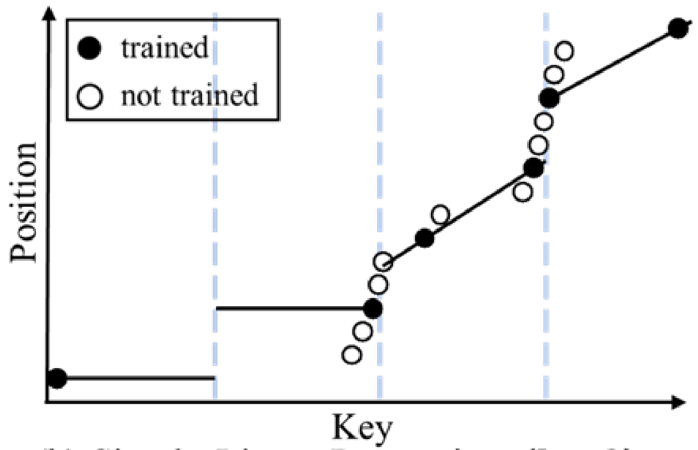
3. Design

2. Sample Learning Algorithm

- Simple Linear Regression
  - The model itself cannot guarantee the error-bound regardless of sampling
    - ➢ To guarantee error bounds, measuring the error of all data causes complete traversal
  - Train sample I^{th} keys → Accuracy can decrease but the error-bound property doesn't change



(a) Simple Linear Regression (I = 1)

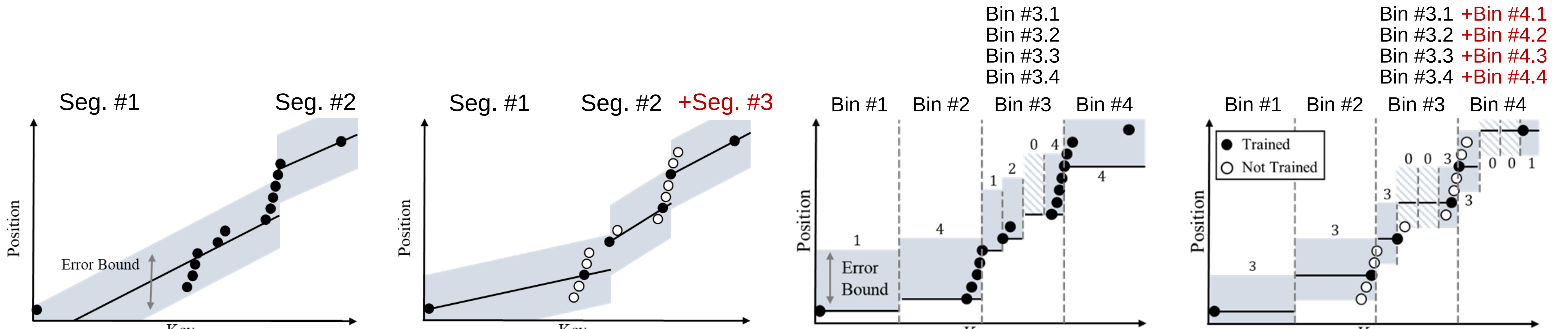


(b) Simple Linear Regression (I = 3)

3. Design

3. Internal Changes due to Sampling

- Depend on segmentation manner
  1) Dynamic segmentation (EB-PLA, EB-Histogram)
     - ➢ Definition: Dynamically segment key ranges according to the distribution
     - ➢ Trade-off: Decrease build time but aggressive sampling can increase # of segments (bins)

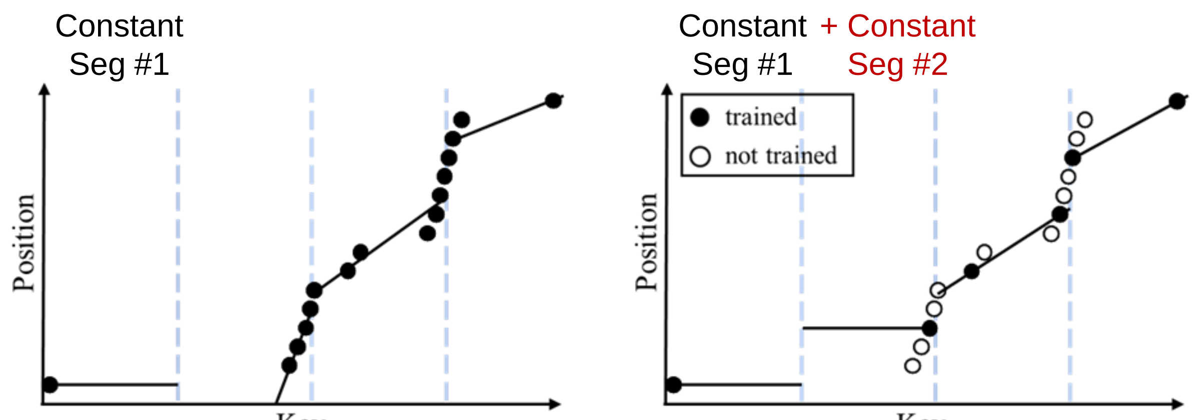


(a) EB-PLA ($I = 1, \varepsilon = 3$) (b) Sample EB-PLA ($I = 1, \delta = 1, \varepsilon = 3$) (a) EB-Histogram ($I = 1, \varepsilon = 5$) (b) Sample EB-Histogram ($I = 1, \delta = 3, \varepsilon = 5$)

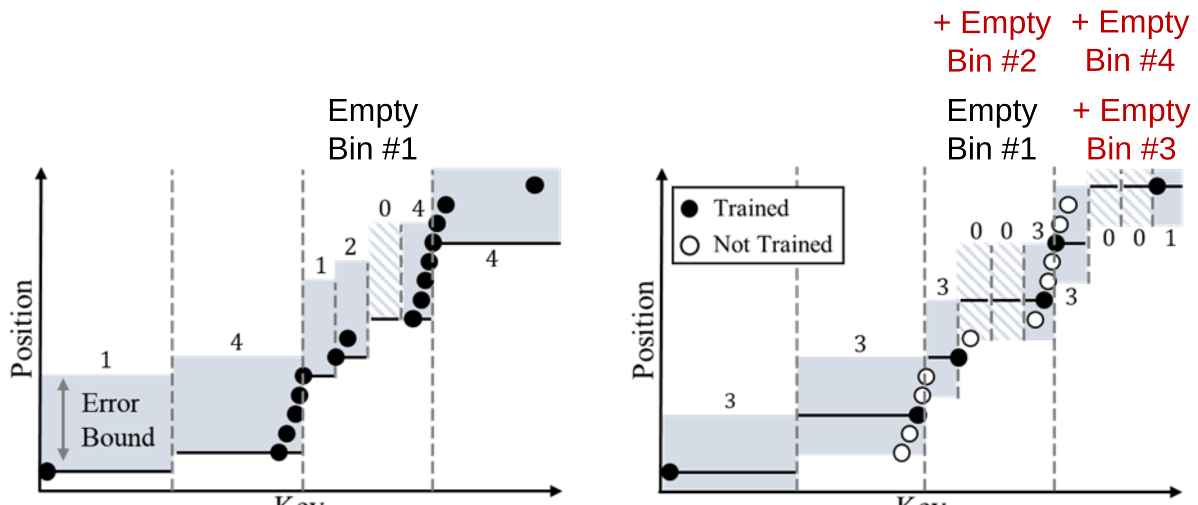
3. Design

3. Internal Changes due to Sampling

- Depend on segmentation manner
  2) Fixed segmentation (Simple Linear Regression, EB-Histogram)
     - ➢ Definition: Segment key ranges into a fixed number of segments
     - ➢ Trade-off: Decrease build time but aggressive sampling can increase # of underfitting segments



(a) Simple Linear Regression (I = 1) (b) Simple Linear Regression (I = 3)



(a) EB-Histogram $(I = 1, \varepsilon = 5)$ (b) Sample EB-Histogram $(I = 1, \delta = 3, \varepsilon = 5)$

4. Evaluation Setup

BASIL (Benchmark of Sampling Applied Learned Indexes)

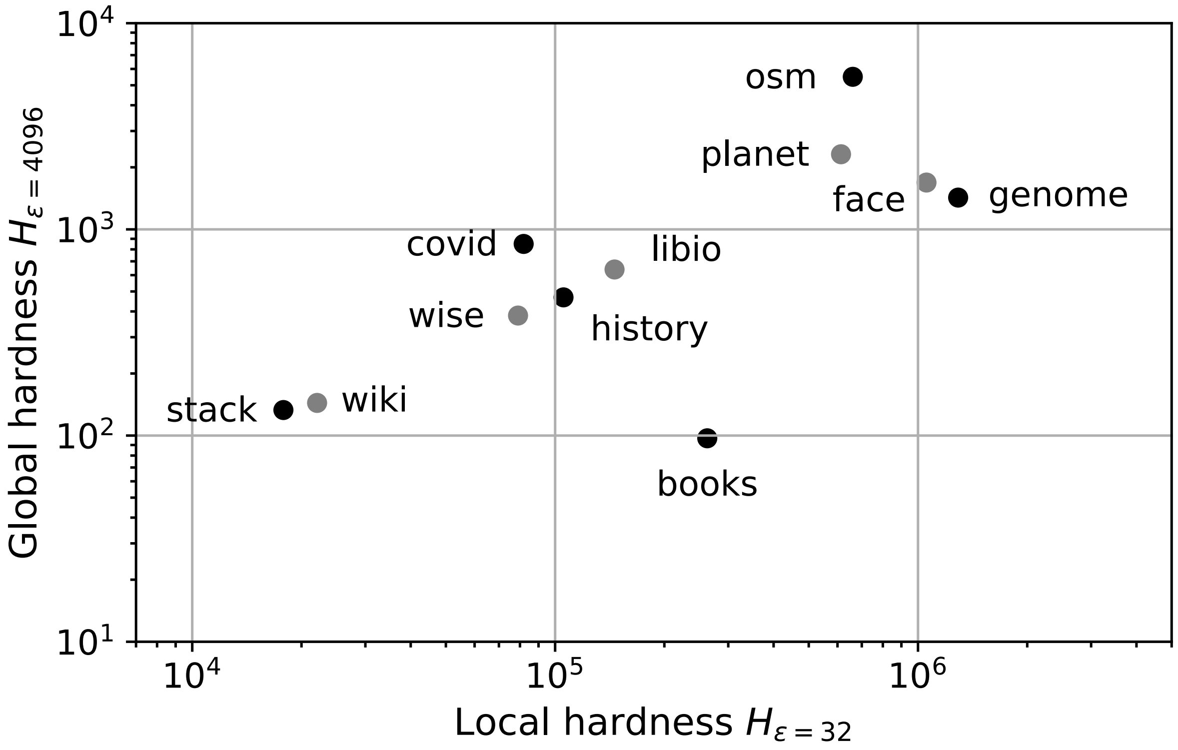
- Applied sampling to 7 indexes, prefixed with "**s**"
  - 3 Learned, 2 Histogram, 3 Tree-based indexes

Type	Index	Internal Model	Correction Search
Learned	sRMI	Simple Linear Regression	Exponential Search
Learned	sPGM / sRS	Sample EB-PLA	Binary Search
Histogram	sCHT	Sample EB-Histogram (Equal-width)	
Histogram	sRT	Sample Histogram (Equal-width)	
Tree-based	sART / sB+-Tree/ sIB-Tree	-	

4. Evaluation Setup

BASIL (Benchmark of Sampling Applied Learned Indexes)

- Datasets: 6 representative datasets with 200 million key-value pairs
- Workload: Lookup uniform random 10 million keys from the dataset.
- Environment: Intel(R) Xeon(R) Gold 6338 CPU 2.00 GHz, 48 MB L3 cache with 512 GB of main memory



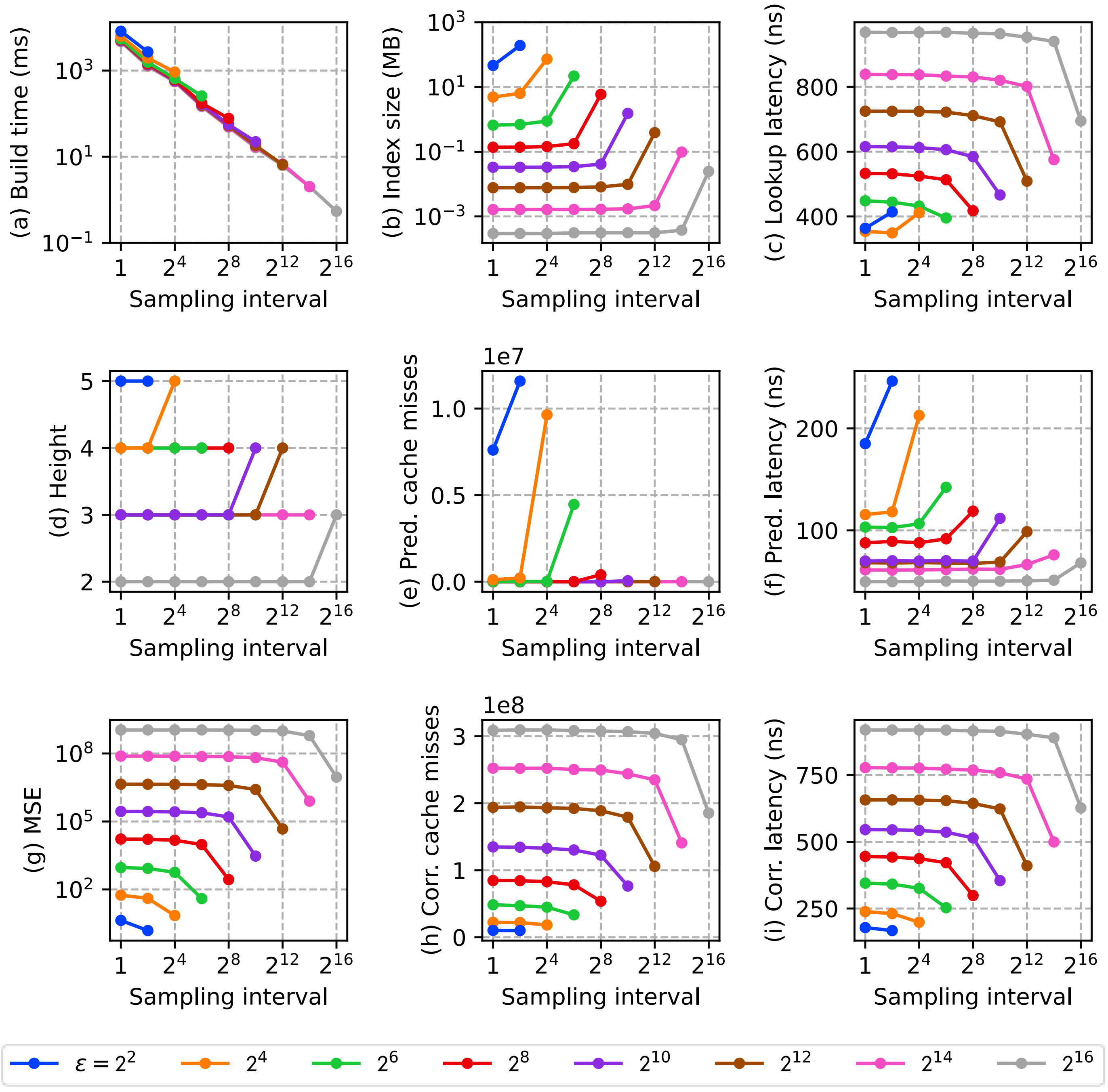
5. Evaluation

1. Sampling Trade-offs

- Index
  - sPGM (Sample EB-PLA)

- Metrics
  - Index: (a) Build Time, (b) Size, (c) Latency, (f) Pred. latency, (i) Corr. latency
  - Model: (d) Height, (g) MSE (Accuracy)
  - Micro-architecture: (e) Pred. Cache Miss, (f) Corr. Cache Miss

Dataset: History, Error bound ($\varepsilon \in [2^2, 2^{16}]$), Sampling interval ($I \in [2^0, \ \varepsilon\ (\le 2^{16})]$)

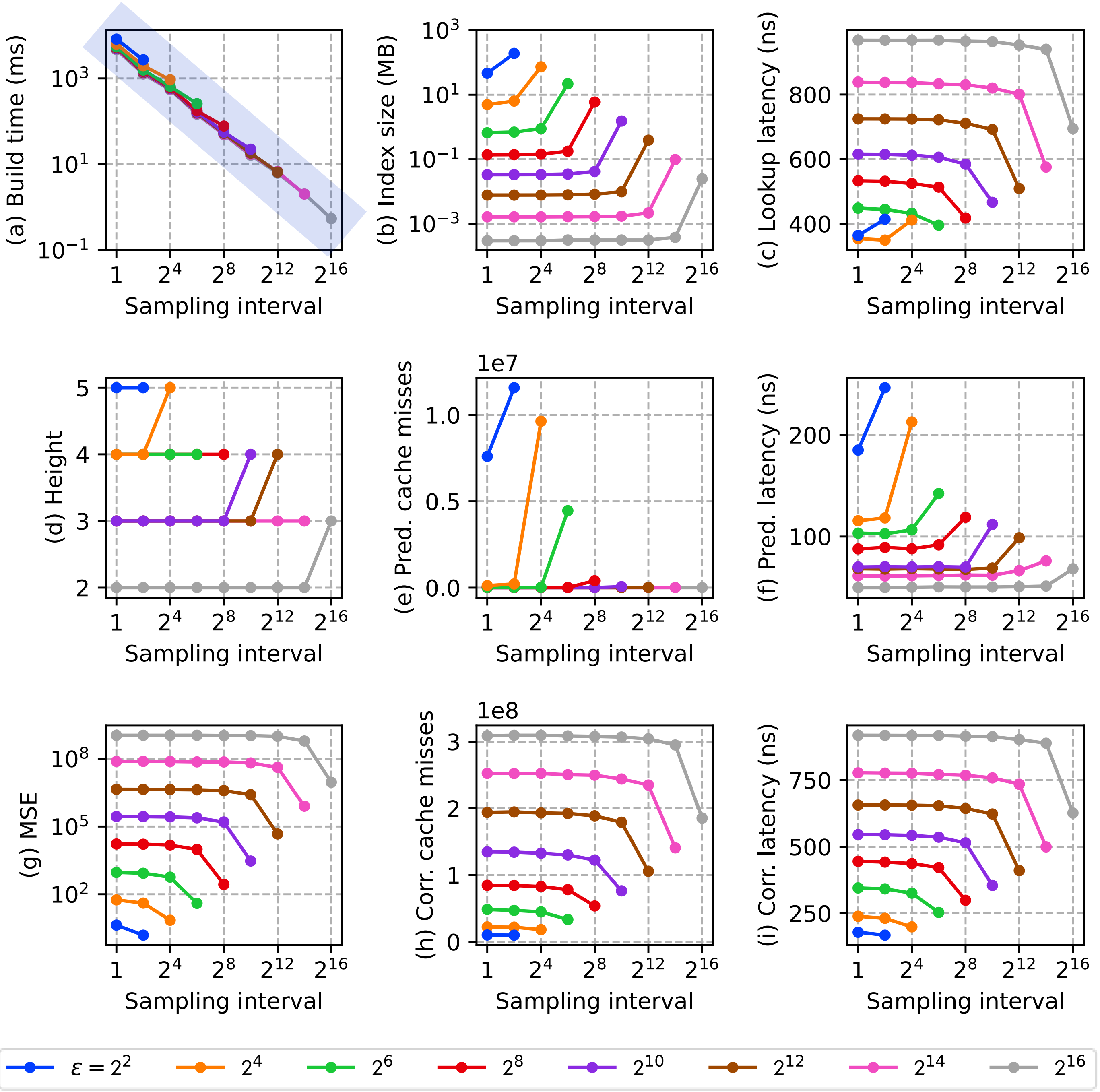


5. Evaluation

1. Sampling Trade-offs

- When sampling interval (I) increases, **(a) build time decreases** by order of magnitude

Dataset: History, Error bound ($\varepsilon \in [2^2, 2^{16}]$), Sampling interval ($\mathrm{I} \in [2^0, \varepsilon\ (\leq 2^{16})]$)



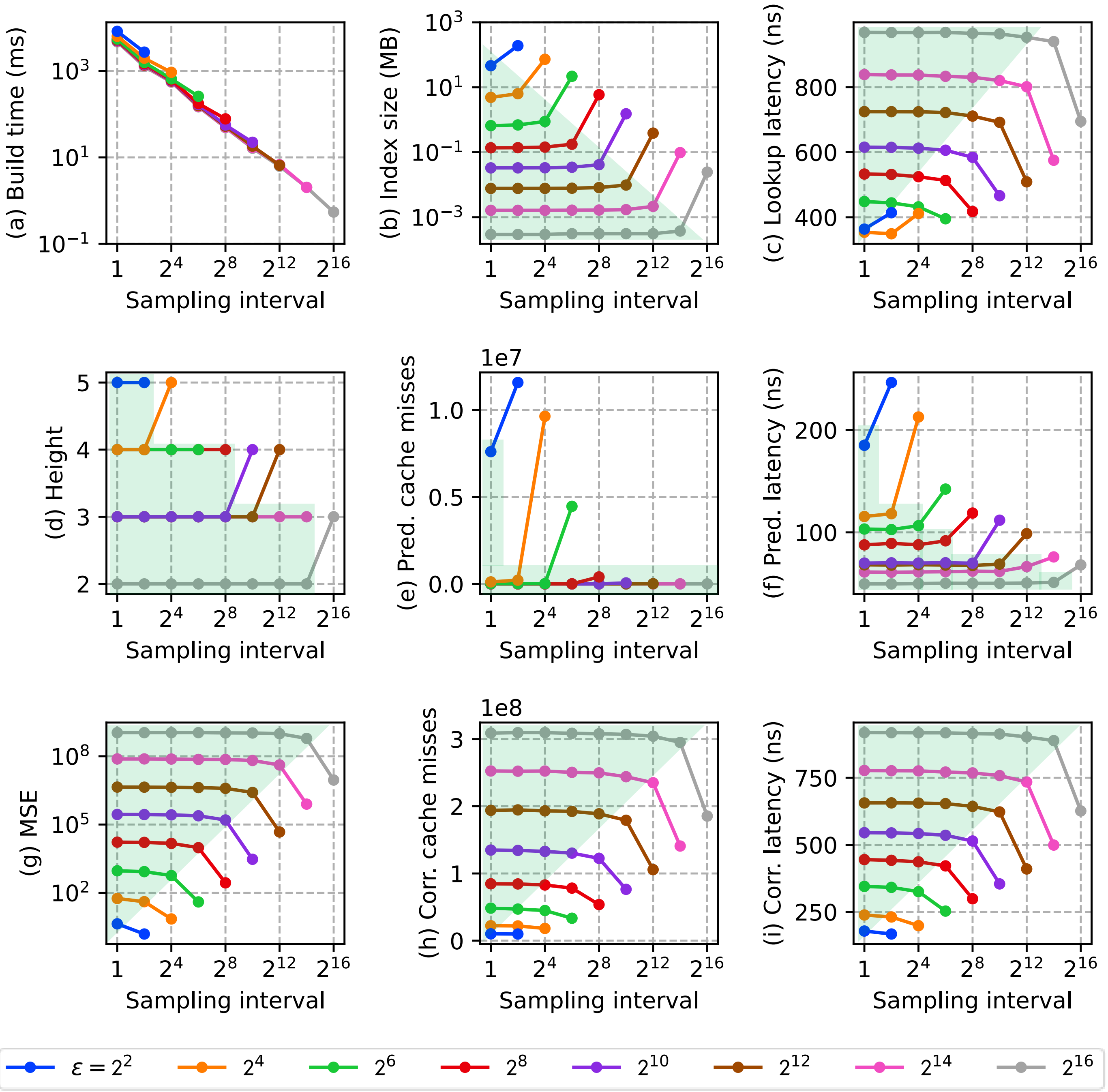
5. Evaluation

1. Sampling Trade-offs

- Each error-bound has a **threshold interval ($\boldsymbol{I_{TH}}$)**
  - mostly $\varepsilon = I^{TH}$

- **Until $\boldsymbol{I_{TH}}$,** (b-i) the rest of metrics **remain consistent**

Dataset: History, Error bound ($\varepsilon \in [2^2, 2^{16}]$), Sampling interval ($\mathrm{I} \in [2^0, \ \varepsilon\ (\leq 2^{16})]$)



5. Evaluation

1. Sampling Trade-offs

- **After I_{TH},**

  # of linear segments ↑

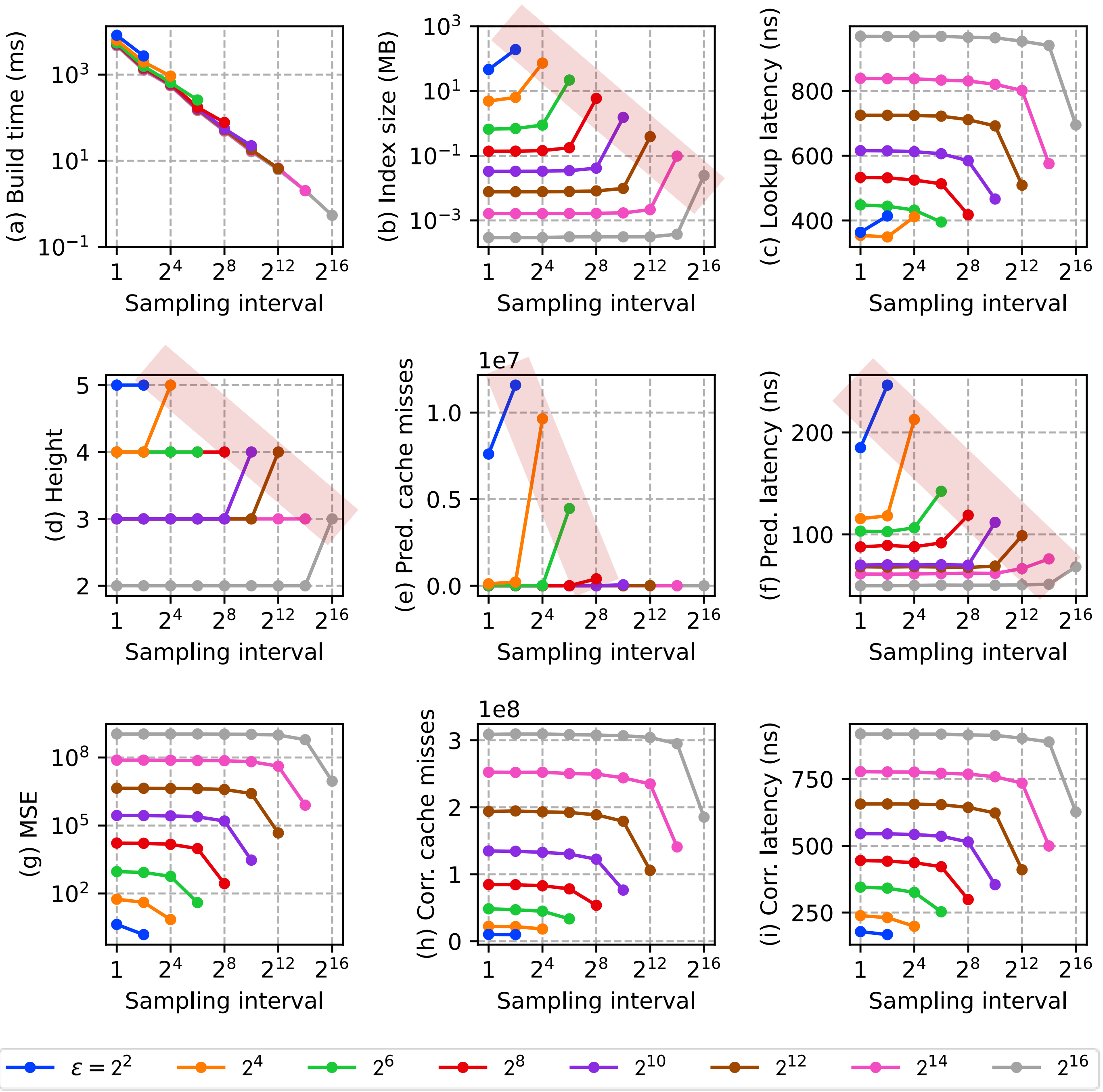
  → (b) Size ↑

  (d) Height ↑

  → (e) Pred. cache miss ↑,

  (f) Pred. latency ↑

Dataset: History, Error bound ($\varepsilon \in [2^2, 2^{16}]$), Sampling interval ($\mathrm{I} \in [2^0, \ \varepsilon\ (\leq 2^{16})]$)



5. Evaluation

1. Sampling Trade-offs

- **After I_{TH},**

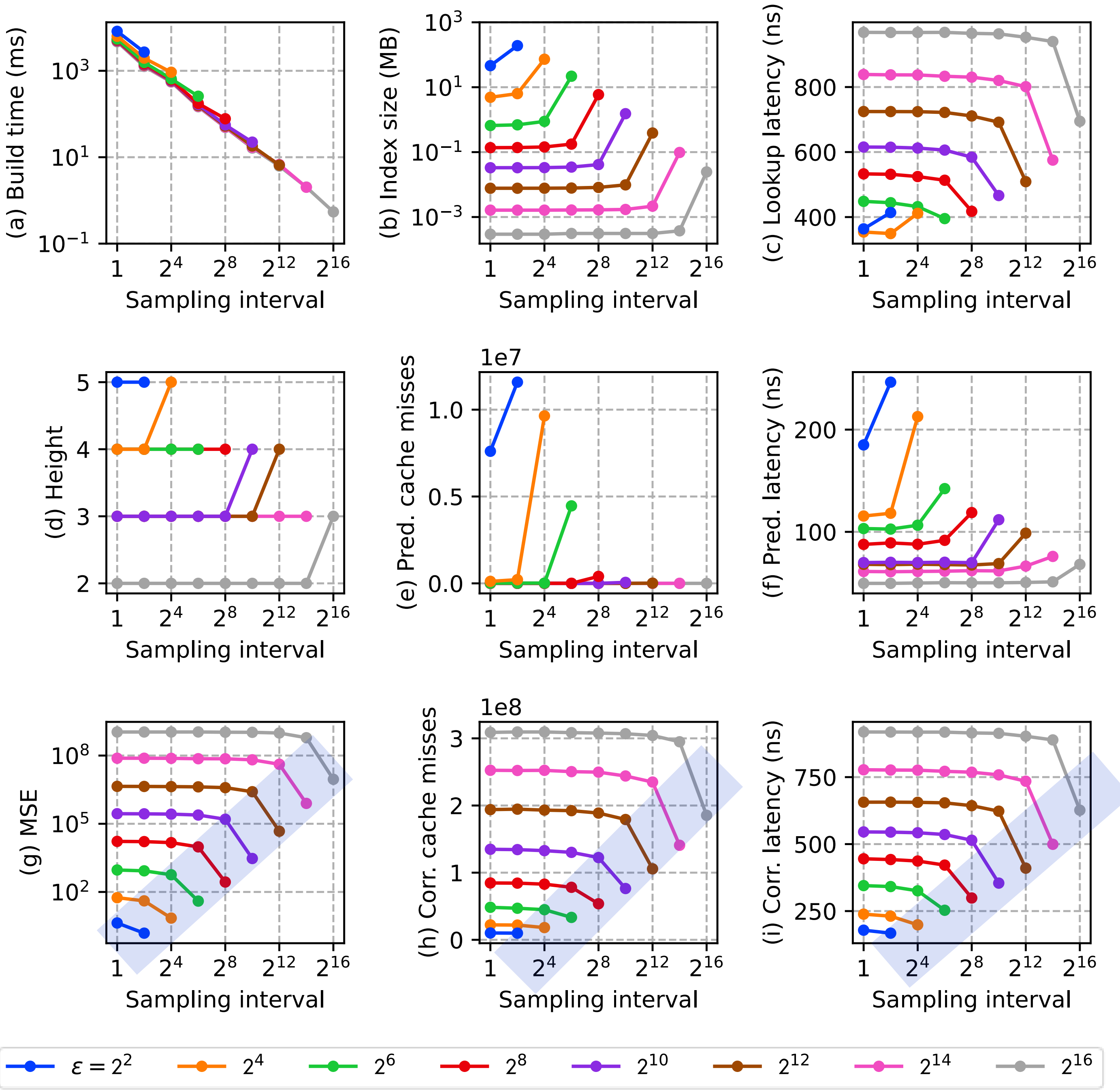
  # of linear segments ↑

  → (g) MSE ↓

  → (h) Corr. cache miss ↓

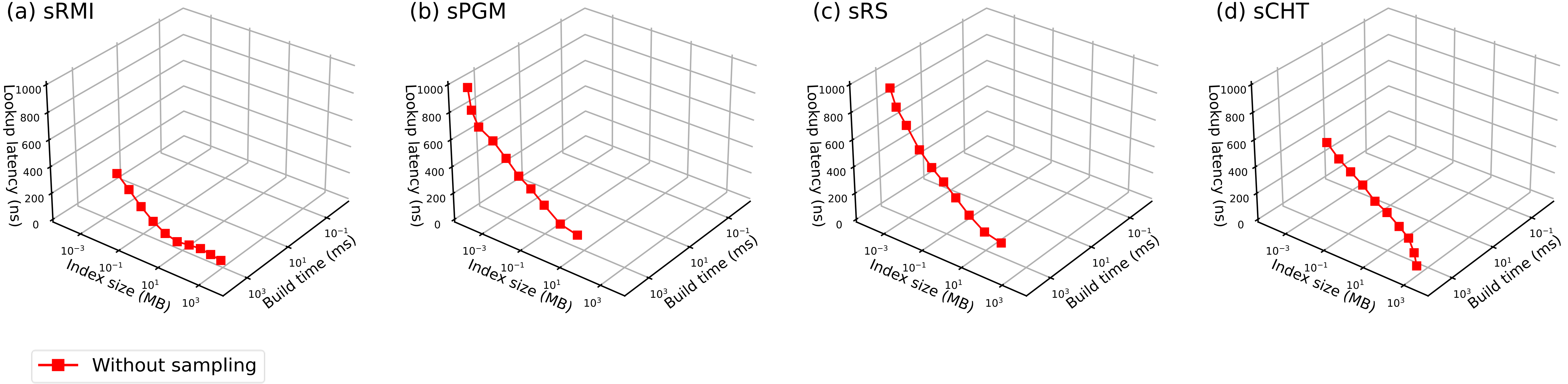
  (i) Corr. latency ↓

Dataset: History, Error bound ($\varepsilon \in [2^2, 2^{16}]$), Sampling interval ($\mathrm{I} \in [2^0, \ \varepsilon\ (\leq 2^{16})]$)



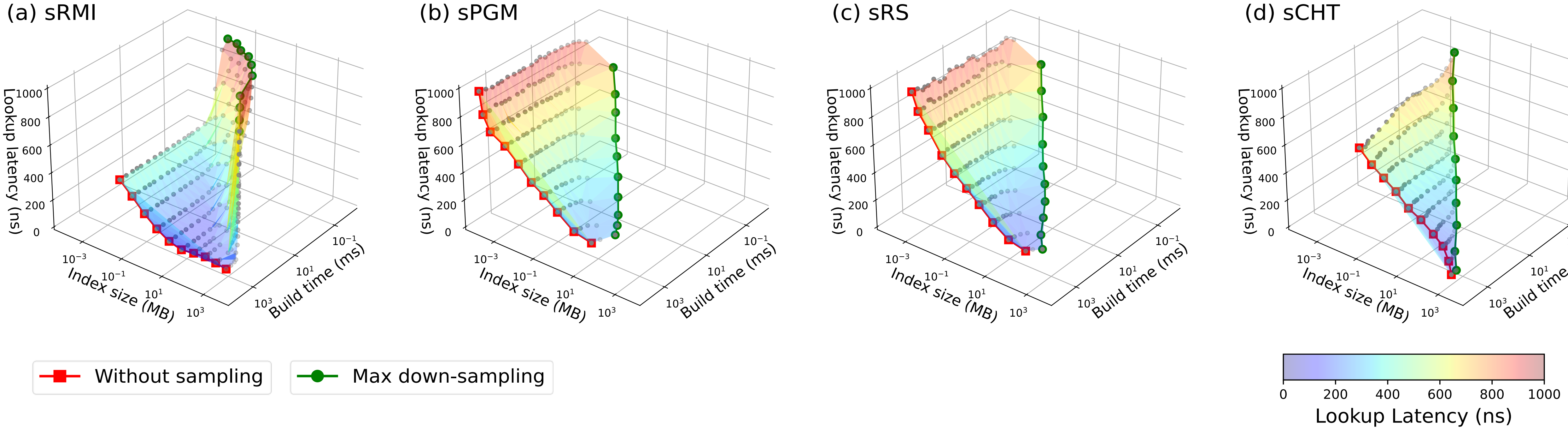
5. Evaluation

- 2. Design Space of Learned Indexes
  - **Absence** of trade-offs between build time, index size, and lookup latency
    - Incurs significant build times regardless of size and lookup latency



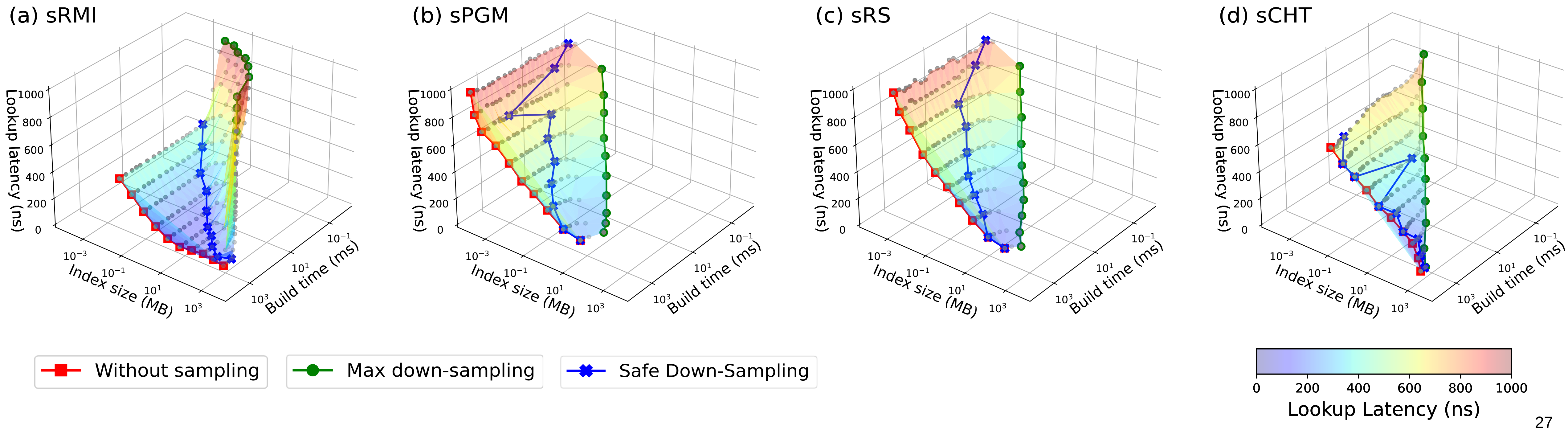
5. Evaluation

- 2. Design Space of Learned Indexes
    - Sampling **introduces** trade-offs between build-time, size, and lookup latency
        - Broadens design space of learned indexes from 2D to 3D



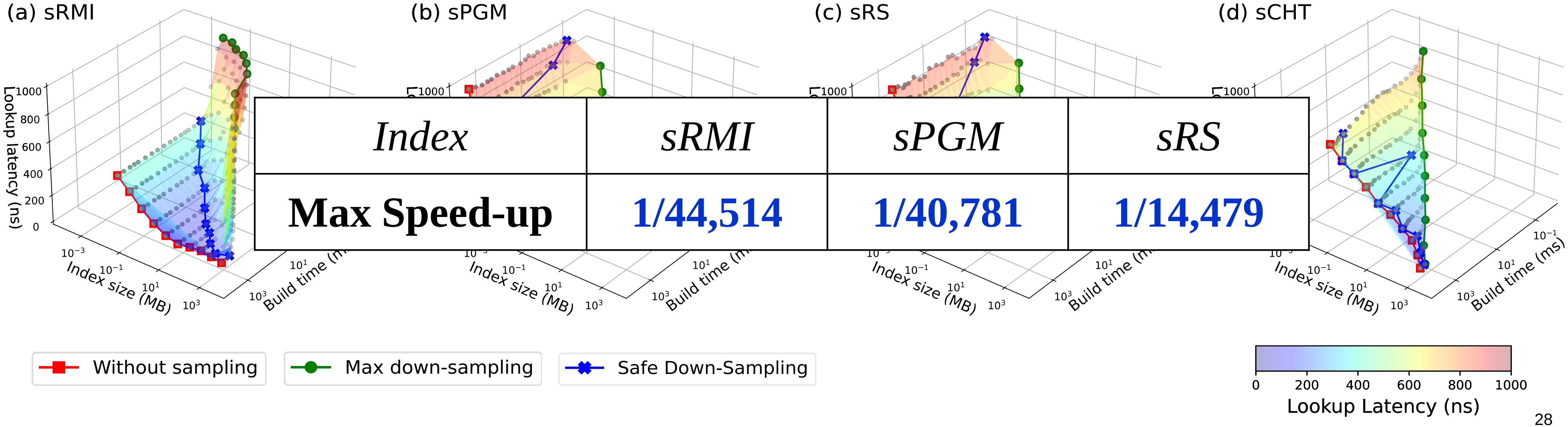
5. Evaluation

- 3. Build Speed-up
  - Question: How much can sampling reduce build time without significantly degrading index performance?
    - ➢ **Safe** down-sampling where size and lookup latency increase by less than 5%



5. Evaluation

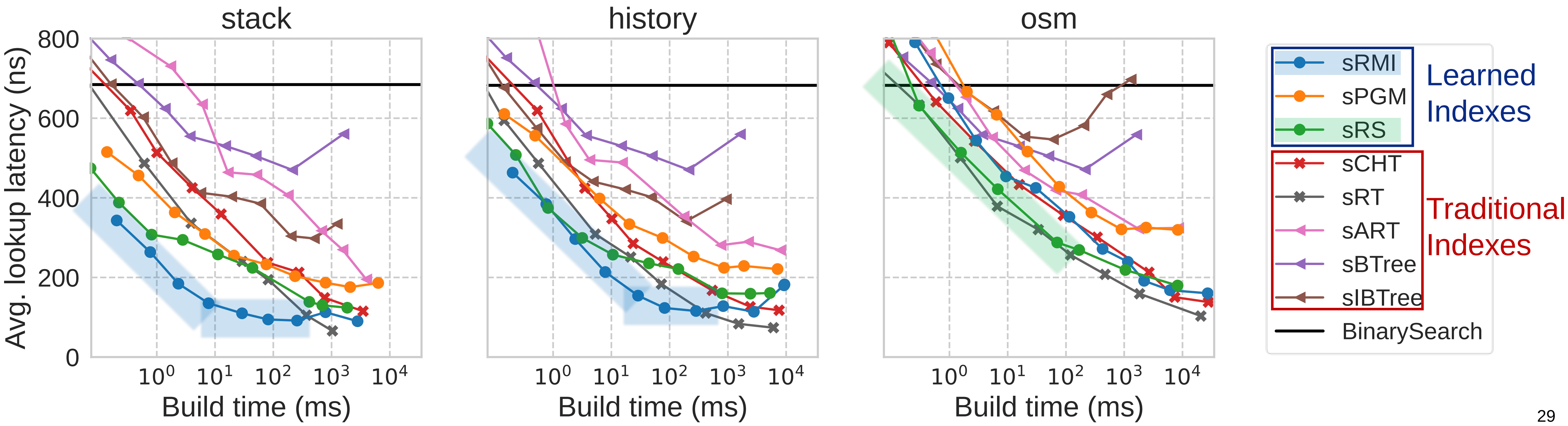
- 3. Build Speed-up
  - Question: How much can sampling reduce build time without significantly degrading index performance?
    - ➢ **Safe** down-sampling where size and lookup latency increase by less than 5%



Index	*sRMI*	*sPGM*	*sRS*
Max Speed-up	**1/44,514**	**1/40,781**	**1/14,479**

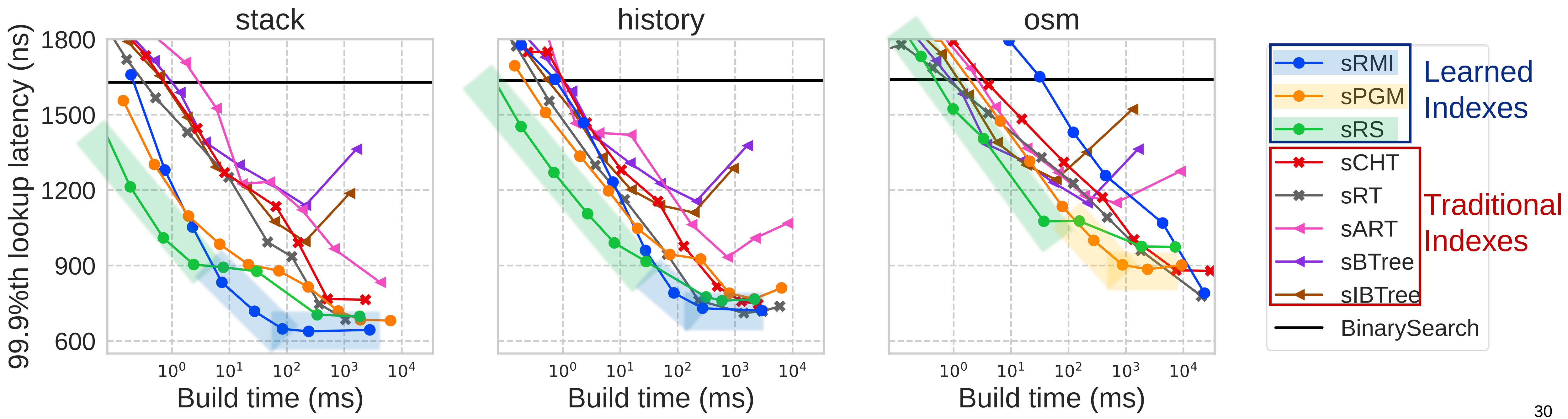
5. Evaluation

- 4. Pareto Optimal Analysis
  - Question: Can learned indexes be built more efficiently than traditional indexes in terms of build time and lookup latency through sampling?
    - **Pareto optimal** (build-efficient) in terms of build time and average lookup latency
      - ➢ no alternative that has both shorter build time and lower average latency



5. Evaluation

- 4. Pareto Optimal Analysis
  - Question: Can learned indexes be built more efficiently than traditional indexes in terms of build time and lookup latency through sampling?
    - **Pareto optimal** (build-efficient) in terms of build time and tail lookup latency
      - ➢ no alternative that has both shorter build time and lower tail latency



6. Conclusion

1. Learned indexes are space-efficient, but long build time make them impractical.

2. Sampling has 3 challenges: 1) losing the error-bound property, 2) absence of benchmark, and 3) complex sampling trade-offs.

3. We propose 1) novel sample learning algorithms that preserve the error-bound, 2) new benchmark, BASIL, and 3) an analysis of sampling trade-offs.

4. We show that sampling can 1) expand the design space, 2) reduce build time without significant performance loss, and 3) build learned indexes efficiently.

Thank you