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

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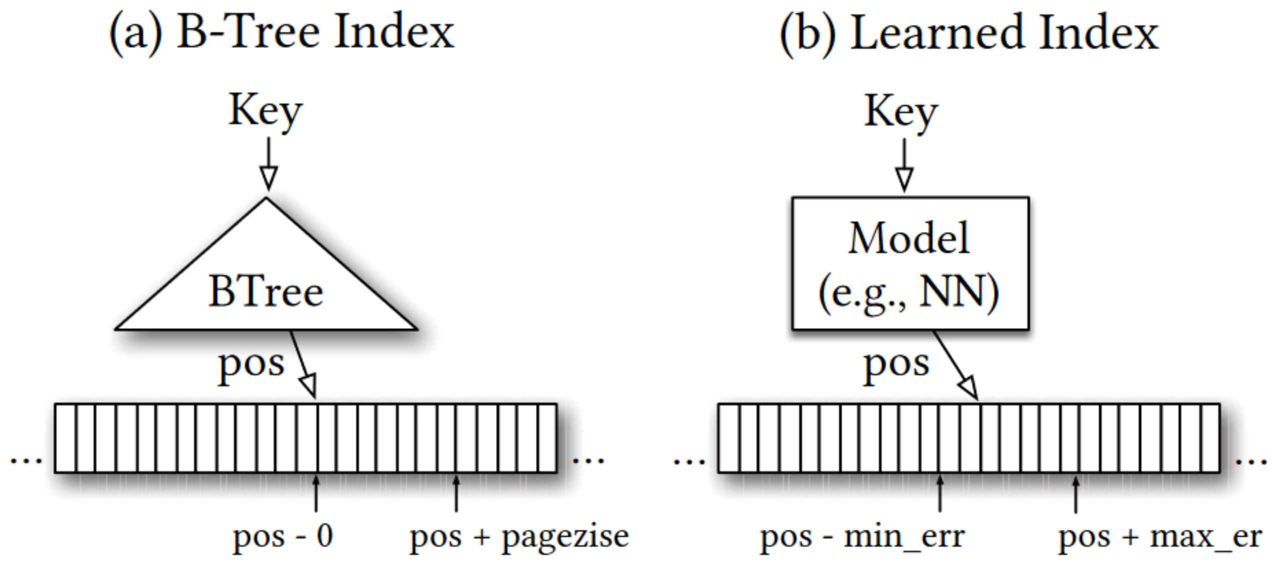
1. Introduction

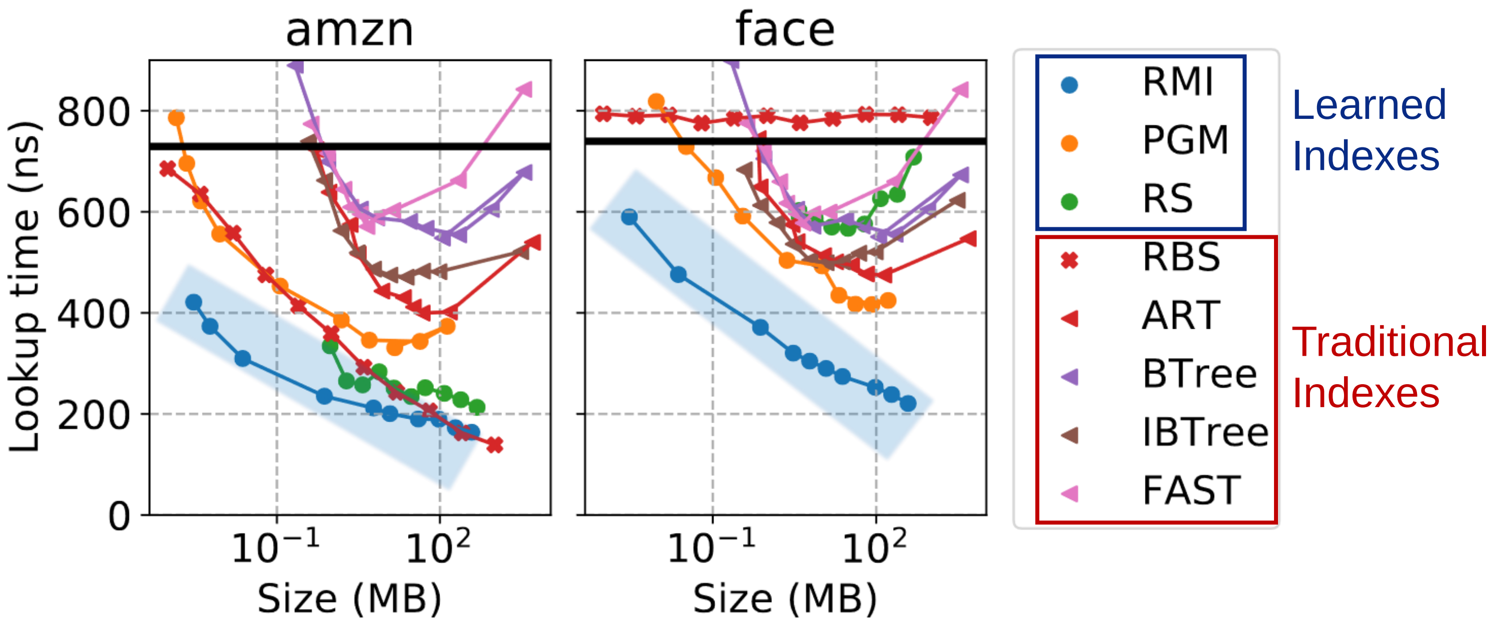
- Learned index
  - Index structure employs machine learning techniques
  - View the index as a model that predicts the position of a key in sorted array



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

1. Introduction

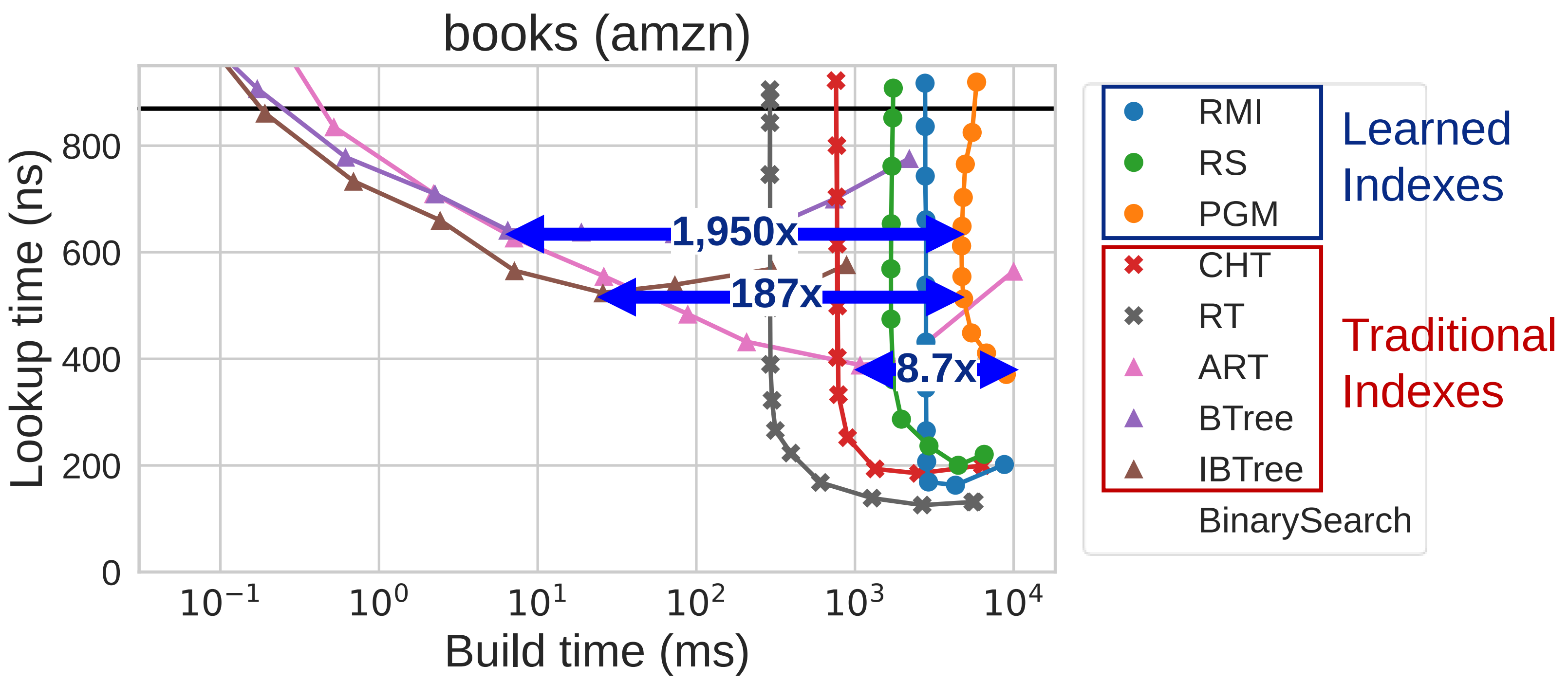
- Learned index
  - Space-efficient by effectively compressing data distribution through model
  - Pareto optimal in terms of index size and lookup latency in read-only workload
    - No alternative exists that has both a smaller size and lower latency



(Benchmarking Learned Indexes, VLDB '20)

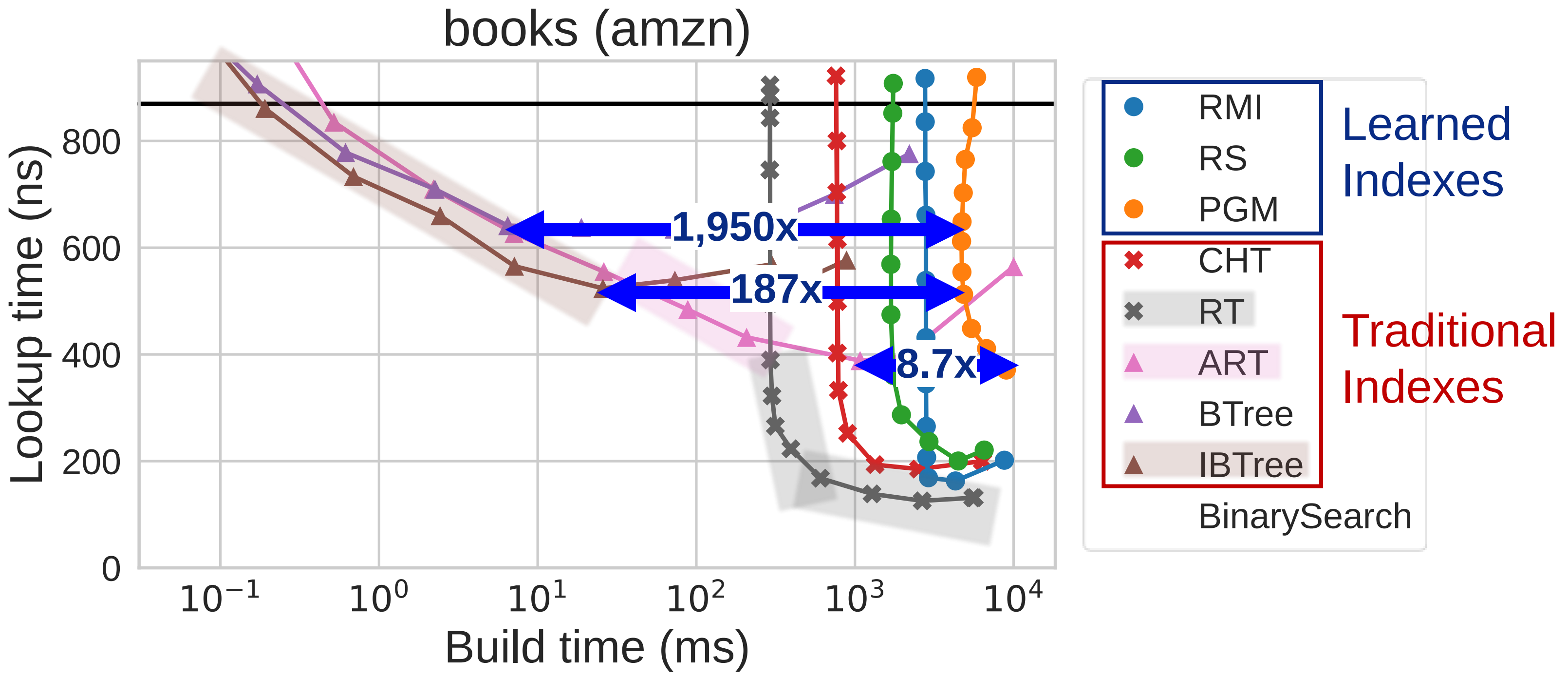
1. Introduction

- Limitation of learned index : **Long index build time**
  - Significantly (up to about 2,000x) longer than traditional indexes



1. Introduction

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

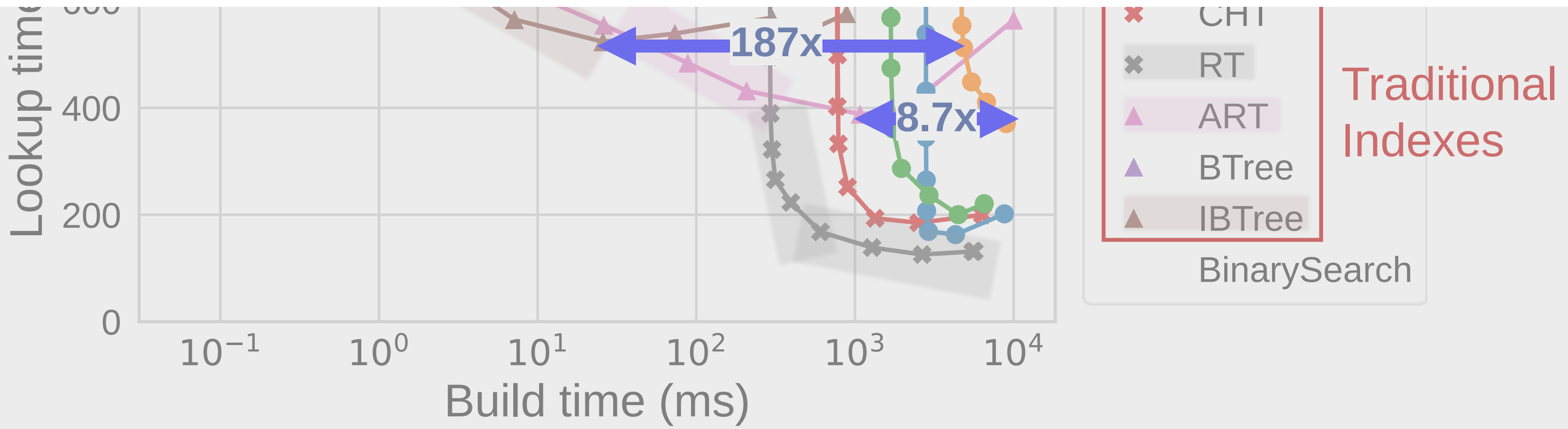


1. Introduction

- Limitation of learned index : **Long index build time**
  - Significantly (up to 1,950x) longer 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

- The primary reason for long build time of learned index

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

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

- To mitigate per-element overhead
  - Light-weight model : RadixSpline (aiDM `20), Bourbon (OSDI `20)
    - It **still** shows longer build time than traditional indexes

1. Introduction

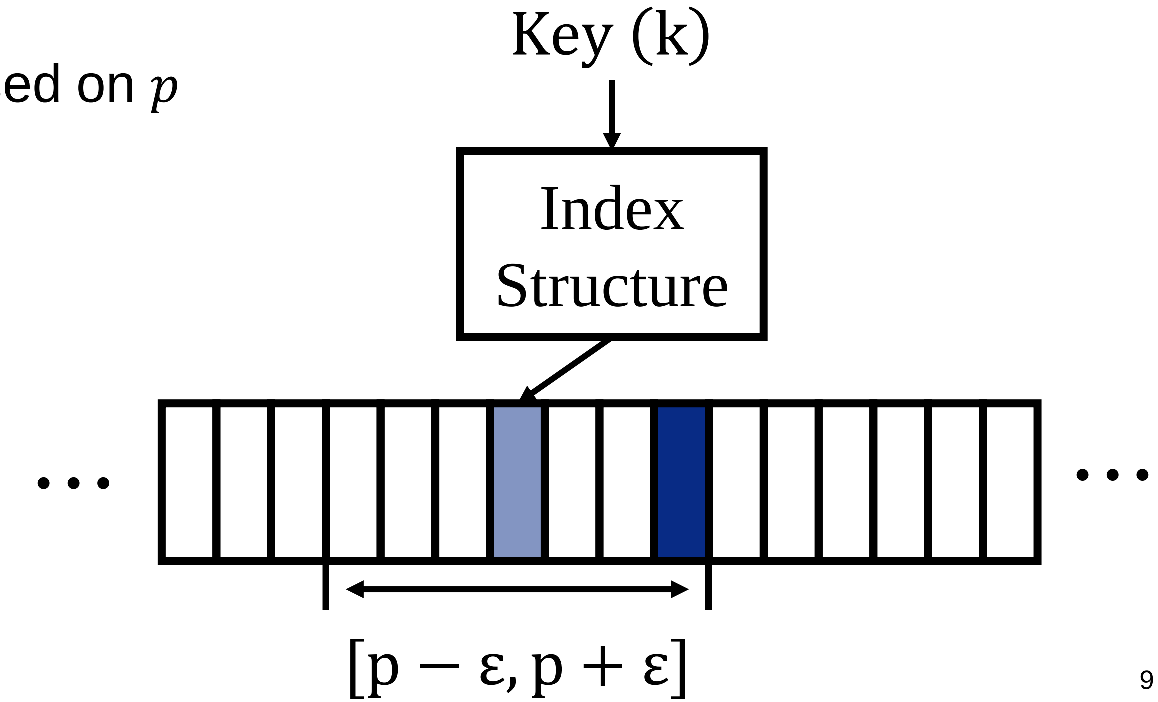
- Our Approach : **Sampling**
  - While sampling may seem simple and even naïve, it is indeed complex

- Challenges

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

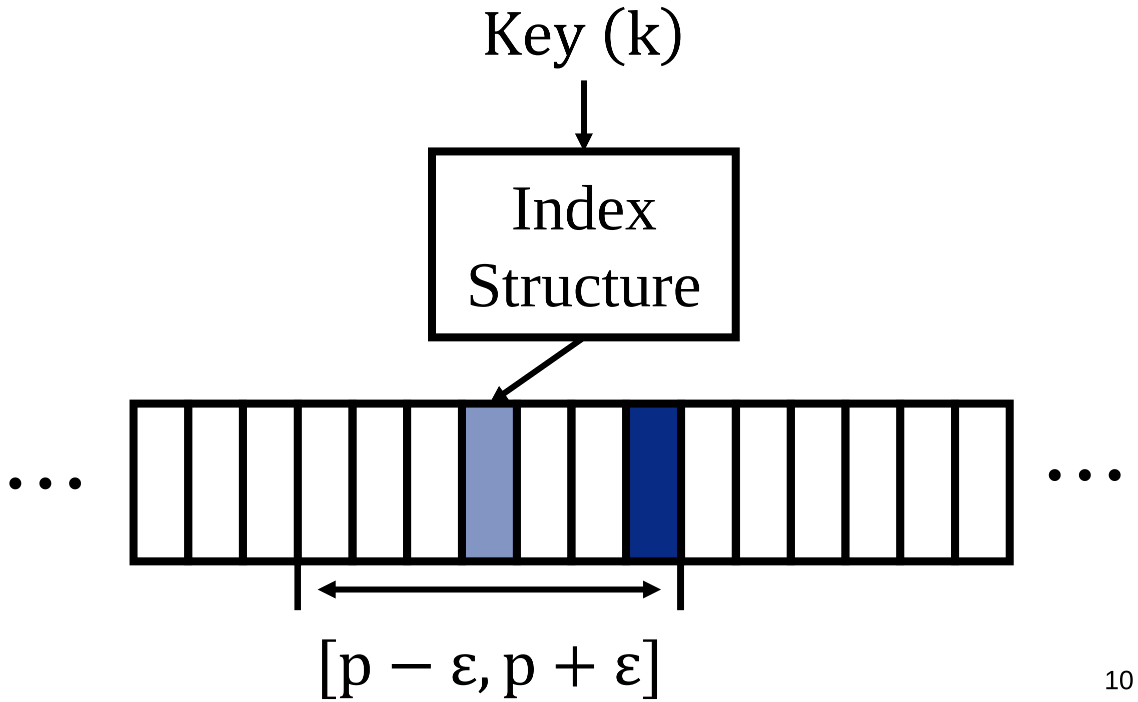
2. Background

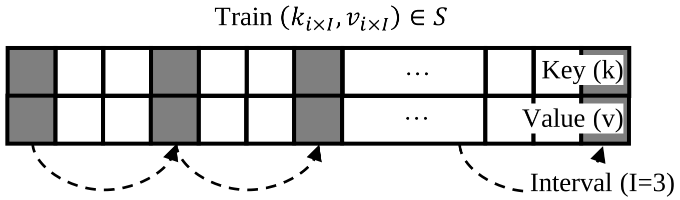
- Workload : Read-only in-memory
  - Practical beginning point of learned index
  - Dataset (D) : Sorted array of unique integer keys without duplicates
  - Lookup : Find the position of a lookup key k in D
    - ① Prediction : Estimate the position of k as p
    - ② Correction : Find the exact position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



2. Background

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





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

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 0-th 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

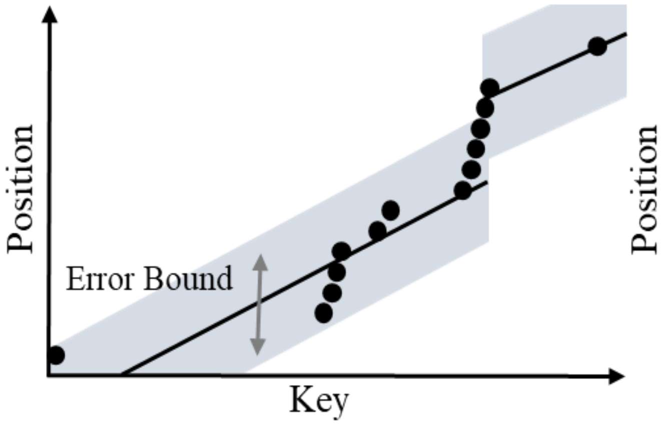
- All indexes access and train only sample key-value data from entire dataset

3. Design

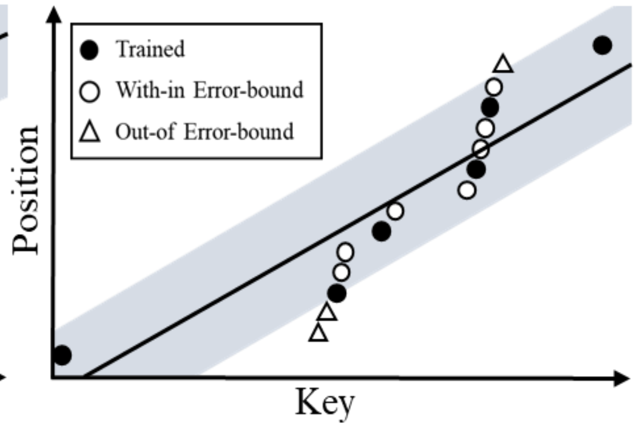
2. Sample learning algorithm

- EB-PLA (Error-bounded Piece-wise Linear Approximation) model
  - Without sampling, model trains all keys with error-bound $\varepsilon \rightarrow Error(k) \leq \varepsilon$
  - With sampling, model trains only sample I^{th} keys with error-bound $\varepsilon \nrightarrow Error(k) \leq \varepsilon$
    - ➢ **Losing** 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 $\varepsilon = 3$

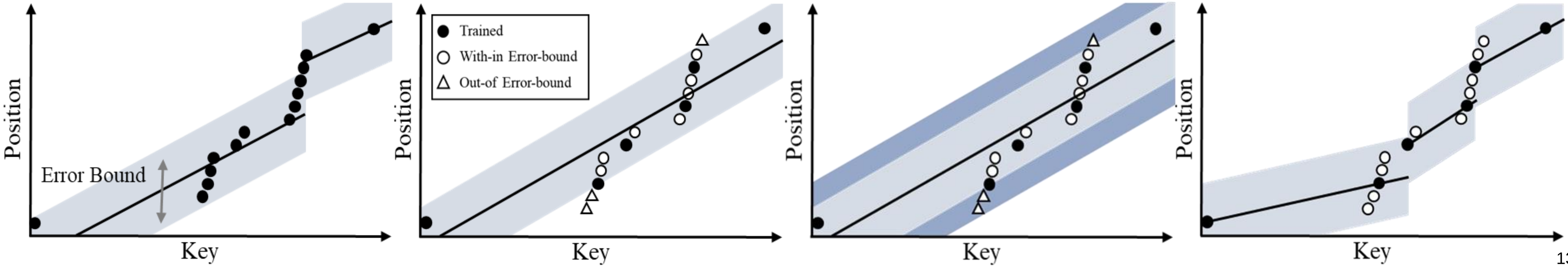


3. Design

2. Sample learning algorithm

- Sample EB-PLA algorithm
  - Refine error-bound due to sampling loss ($\varepsilon' = \varepsilon + I - 1$)
    - ➢ In Fig. (c), preserves error-bound property, but cannot guarantee desired error-bound (ε)
  - Replace the learning error-bound to $\delta (= \varepsilon - I + 1)$ for desired error-bound (ε)
    - ➢ In Fig. (d), preserves error-bound (ε) by learning less data with smaller & stricter error bound

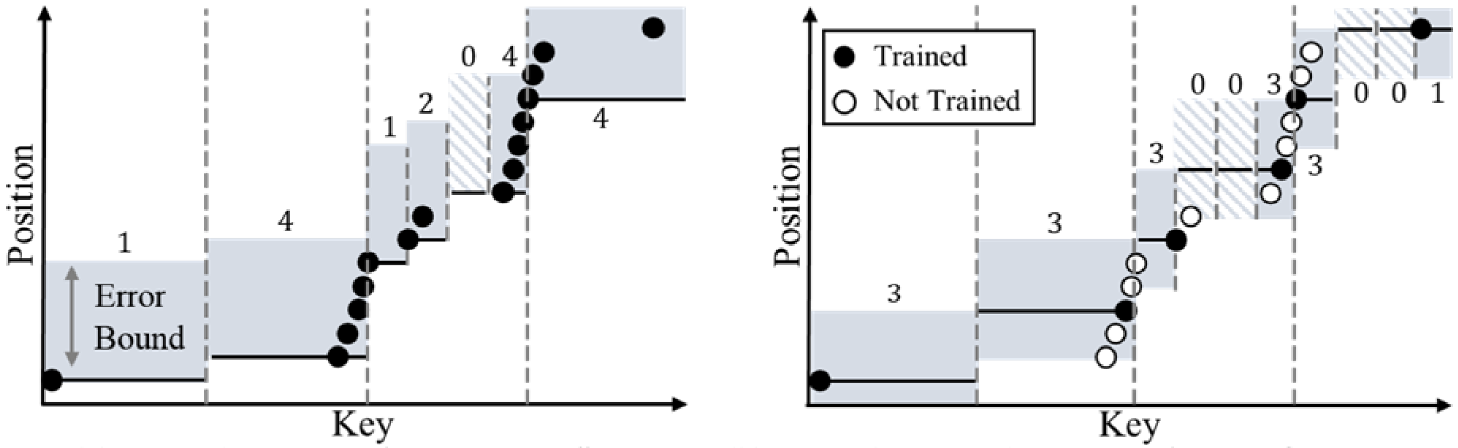
(a) Train All (I = 1) with $\varepsilon = 3$ | (b) Train Sample (I = 3) with $\varepsilon = 3$ | (c) Refine Error-bound ε from 3 to 5 | (d) Train Sample (I = 3) with $\delta = 1$



3. Design

2. Sample learning algorithm

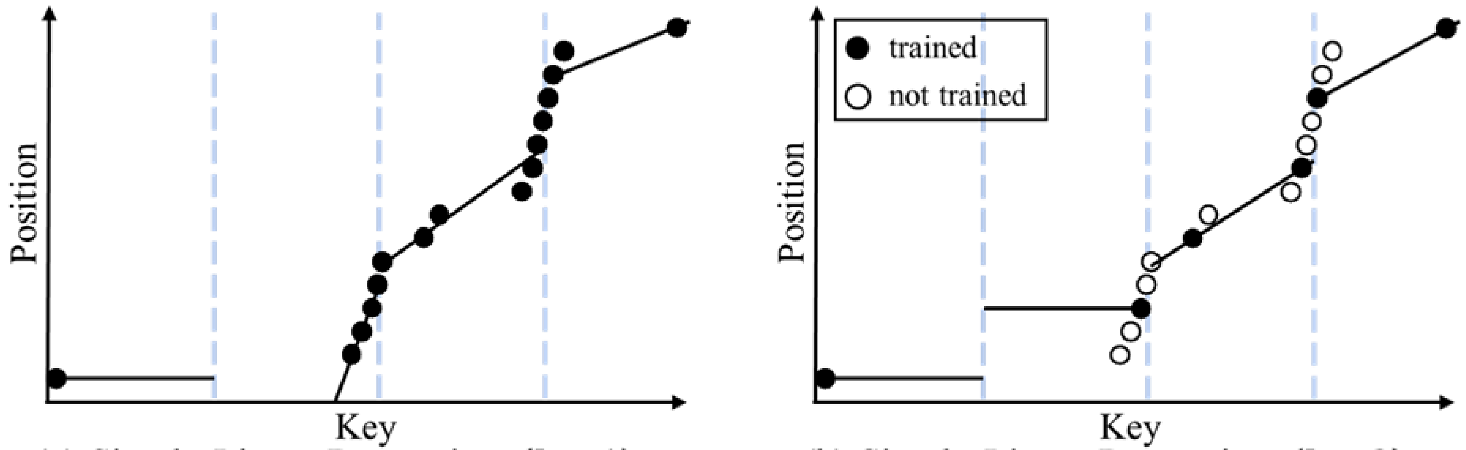
- Sample EB-Histogram algorithm
  - Fig (a), Train all with error-bound $\varepsilon \rightarrow \forall k \in \mathrm{D},\ k \in [p, p+\varepsilon]$
  - Fig (b), Train sample with error-bound δ (=ε−I+1) $\rightarrow \forall k \in \mathrm{D},\ k \in [p-I+1,\ p+\delta]$
    - ➢ Preserve Correction length $(\varepsilon + 1 = \delta + I)$



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

3. Design

2. Sample learning algorithm
   - PLR with Simple Linear Regression
     - Fig. (a), Model itself cannot guarantee an error-bound regardless of sampling
       - ➢ To guarantee error-bound, Measuring all data errors after training causes significant overhead.
     - Fig. (b), Sampling can decrease accuracy(MSE), but error-bound property doesn't change.

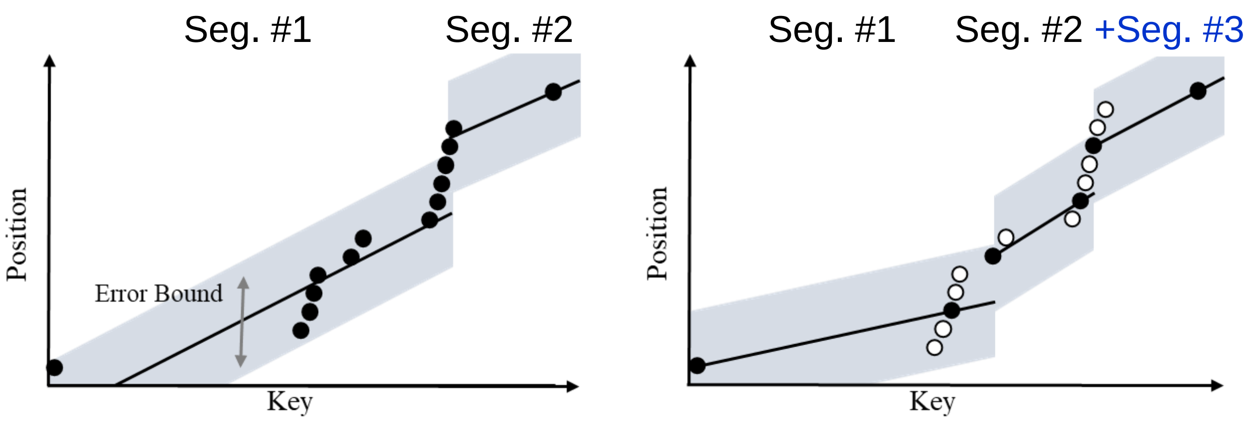


(a) Simple Linear Regression (I = 1) (b) Simple Linear Regression (I = 3)

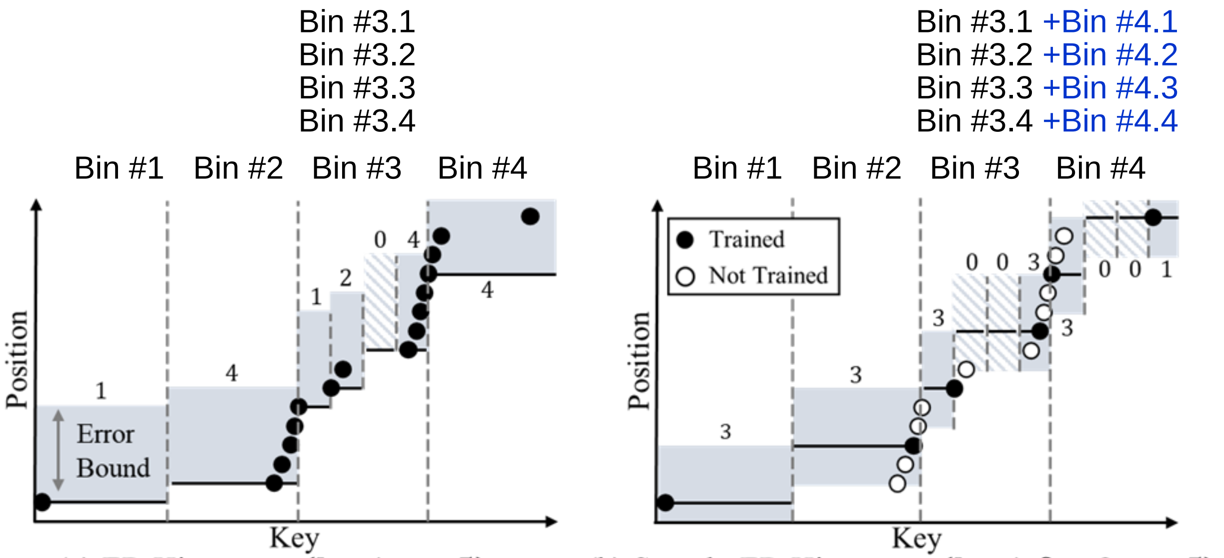
3. Design

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 ($I = 1, \delta = 3, \varepsilon = 5$)

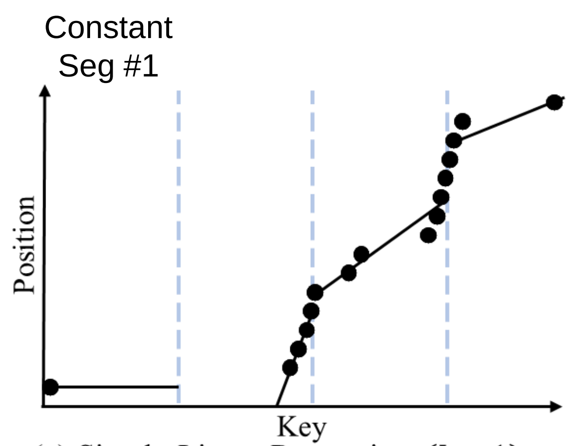
3. Design

3. Internal changes due to sampling

- Depend on segmentation manner

  2) Fixed segmentation (PLR, 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



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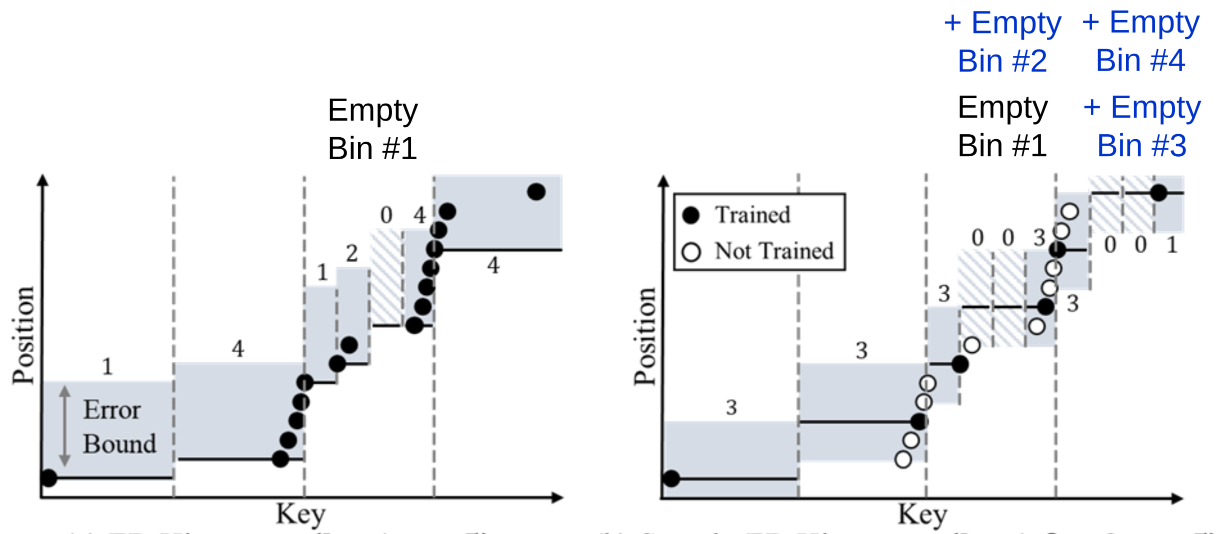


(a) EB-Histogram $(I = 1, \varepsilon = 5)$ (b) Sample EB-Histogram $(I = 1, \delta = 3, \varepsilon = 5)$

4. Evaluation Setup

BASIL (Benchmark of Sampling Applied Learned Indexes)

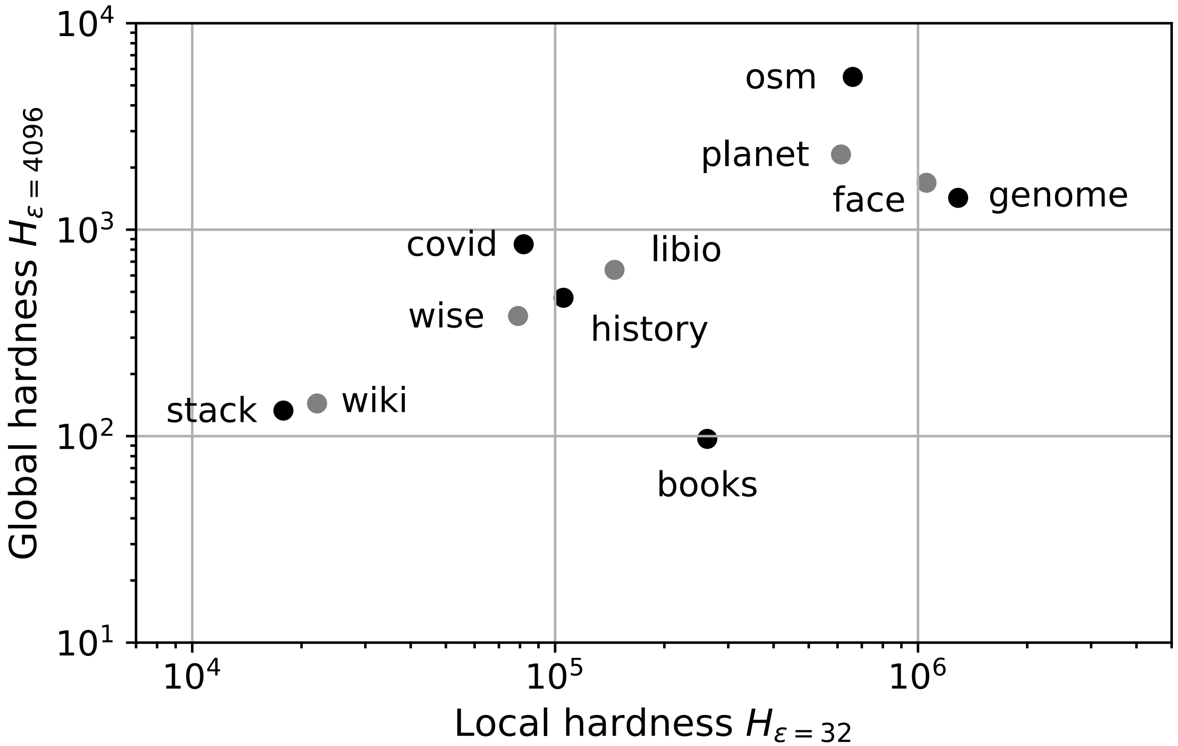
- Applied sampling to 7 indexes, prefixed with **“s”**
  - 3 Learned, 2 Histogram, 3 Tree-based indexes

<table>
<tr><th>Type</th><th>Index</th><th>Internal Model</th><th>Correction Search</th></tr>
<tr><td>Learned</td><td>sRMI</td><td>Simple Linear Regression</td><td>Exponential Search</td></tr>
<tr><td>Learned</td><td>sPGM / sRS</td><td>Sample EB-PLA</td><td rowspan="4">Binary Search</td></tr>
<tr><td>Histogram</td><td>sCHT</td><td>Sample EB-Histogram (Equal-width)</td></tr>
<tr><td>Histogram</td><td>sRT</td><td>Sample Histogram (Equal-width)</td></tr>
<tr><td>Tree-based</td><td>sART / sB+-Tree/ sIB-Tree</td><td>-</td></tr>
</table>

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 with 512 GB of main memory

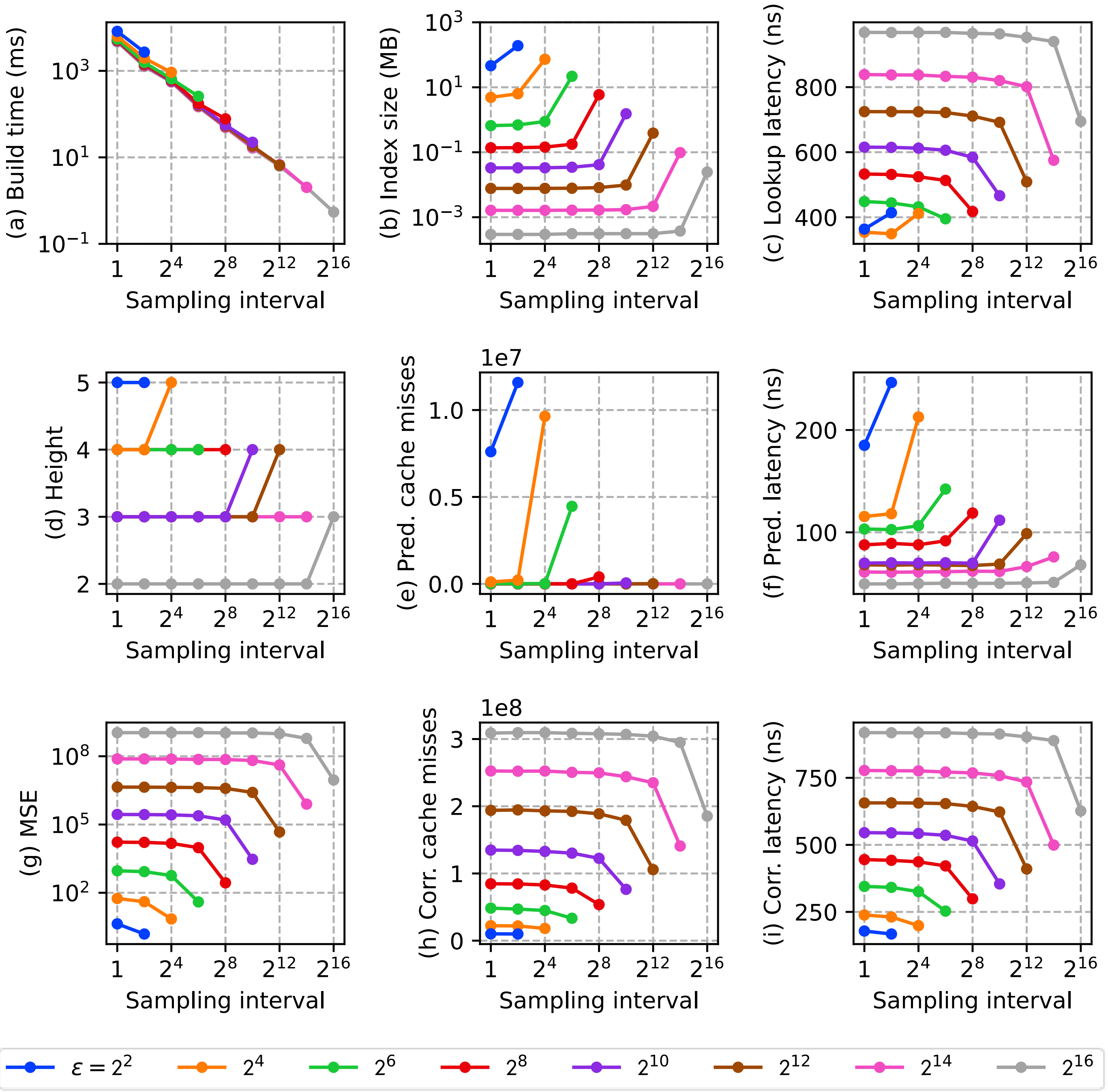


5. Evaluation

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

1. Sampling Trade-offs

- Index
  - sPGM with 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

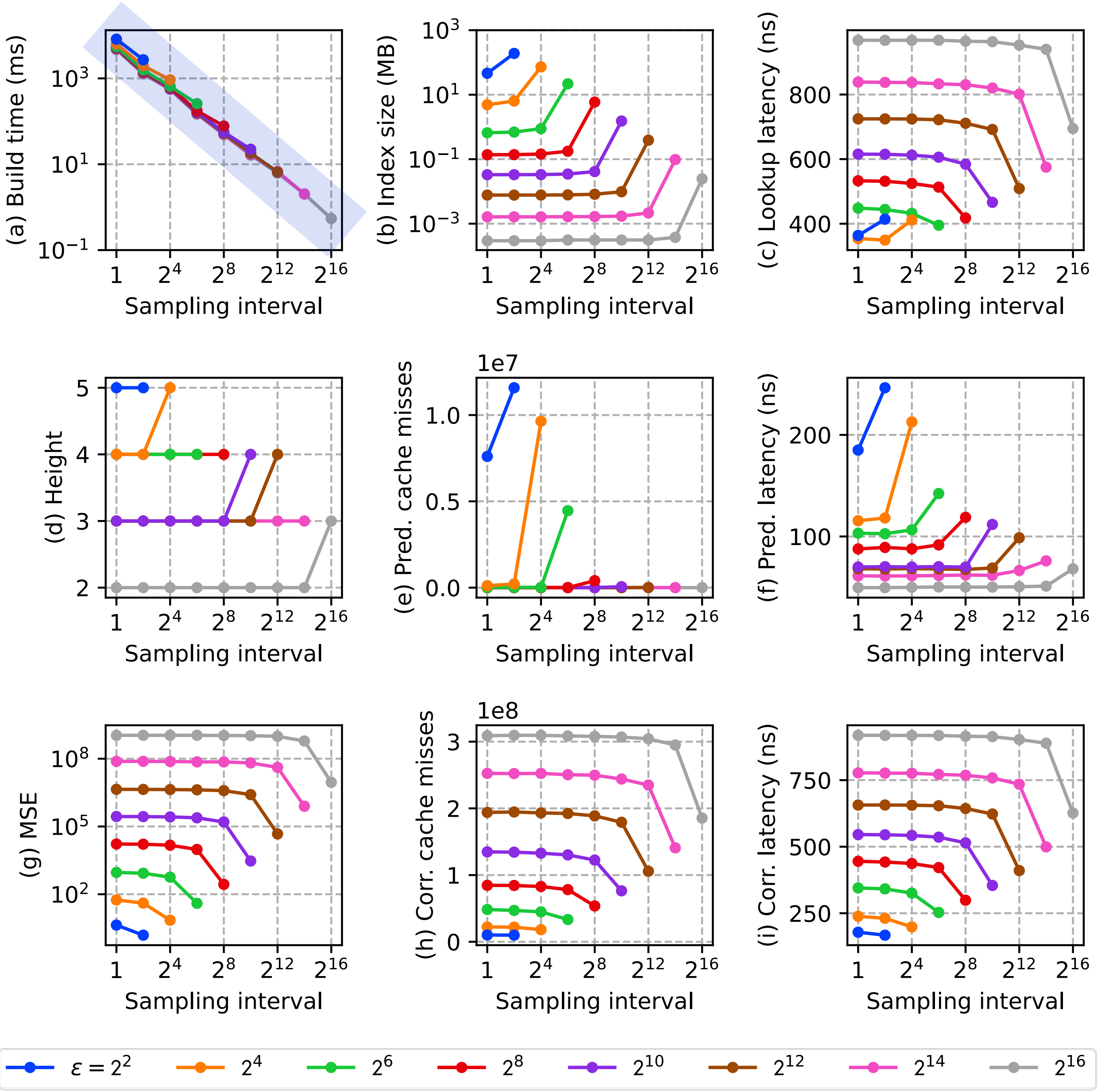


5. Evaluation

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 ($\mathrm{I} \in [2^0, \ \varepsilon (\leq 2^{16})]$)



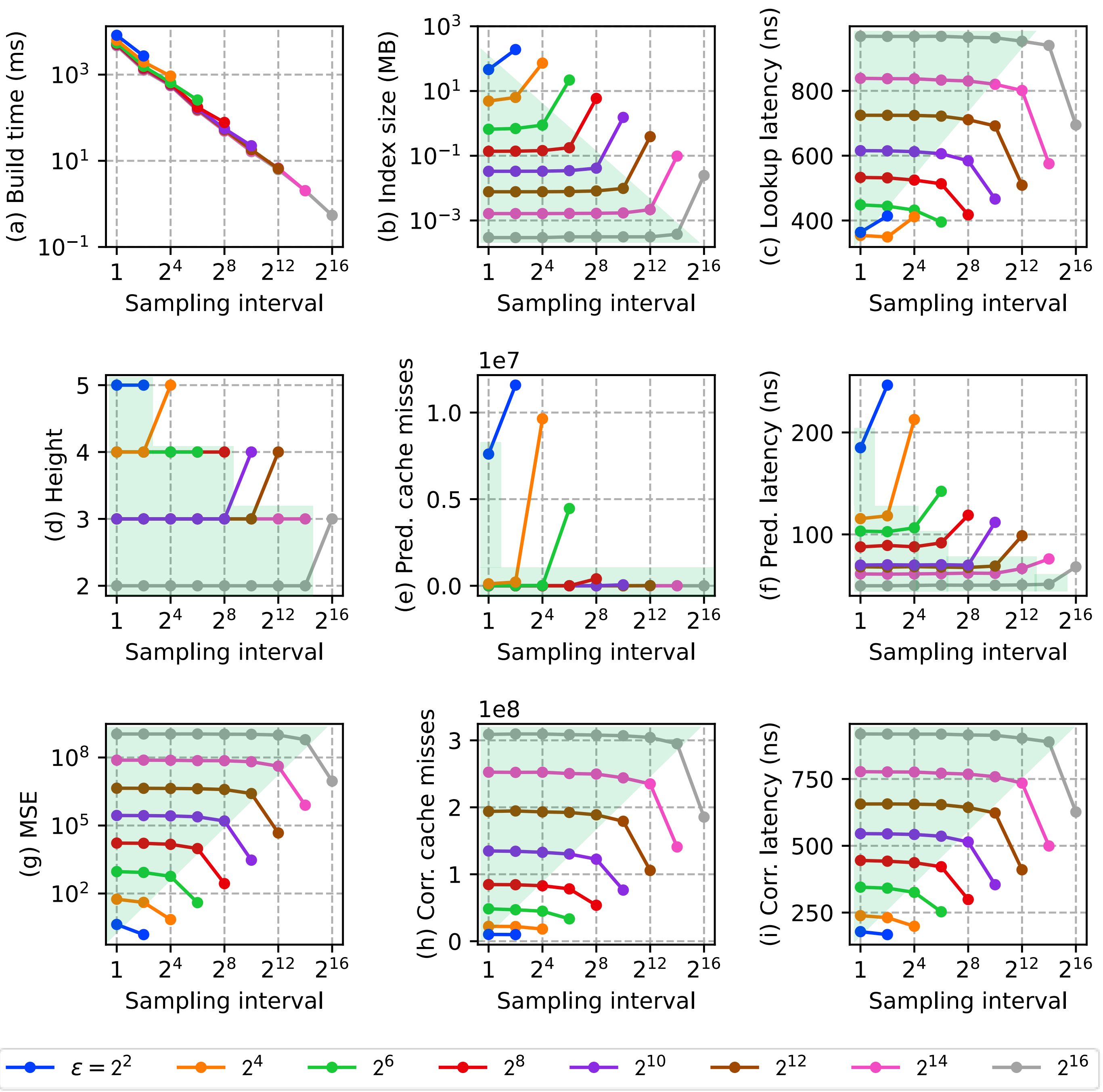
5. Evaluation

1. Sampling Trade-offs

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

- **Until** threshold interval **(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** threshold interval I_{TH},

  # of linear segments ↑

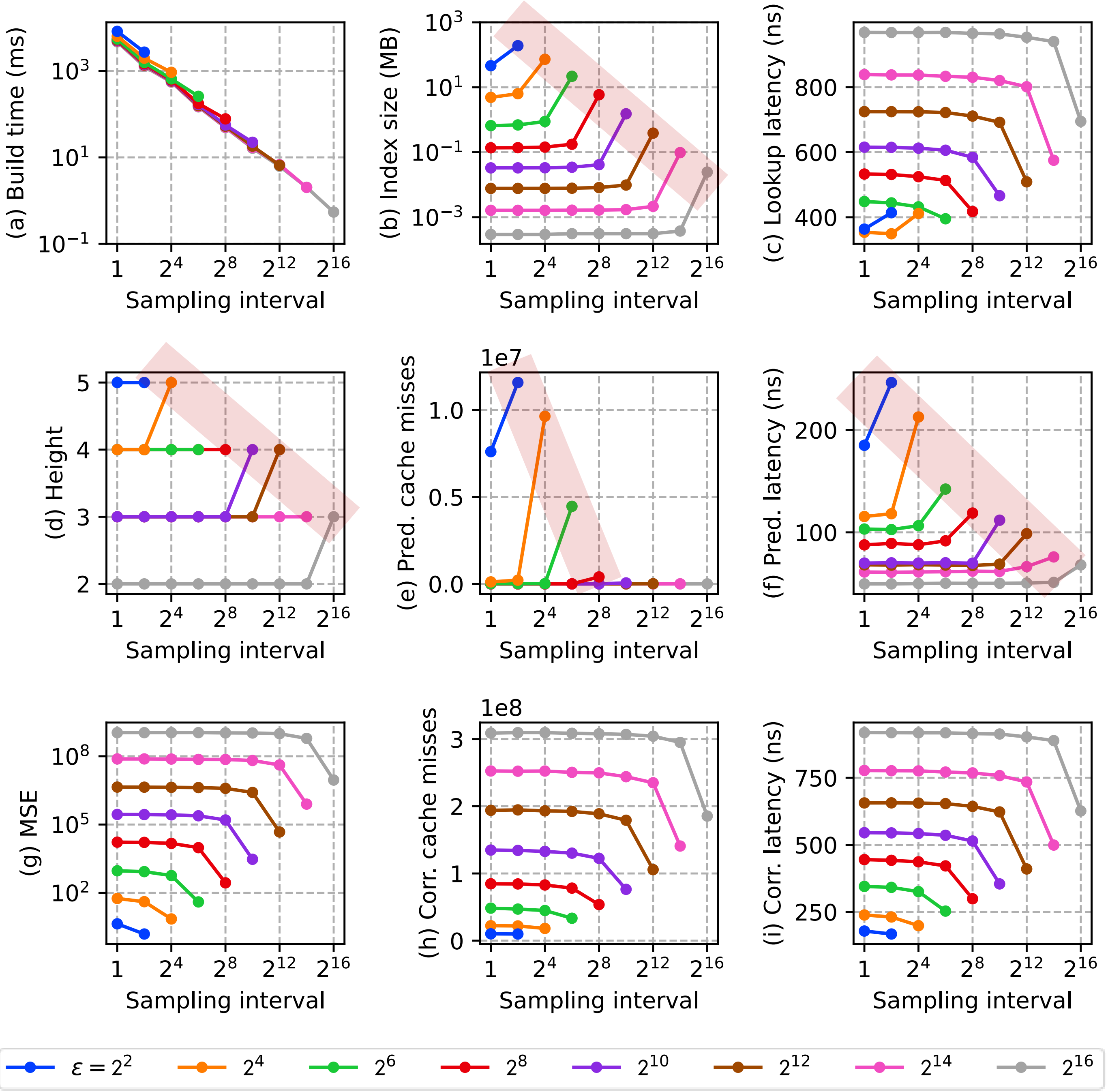
  → (b) Size ↑

  (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** threshold interval $\boldsymbol{I_{TH}}$,

  # of linear segments ↑

  → (g) MSE ↓

  → (h) Corr. cache miss ↓

  (i) Corr. latency ↓

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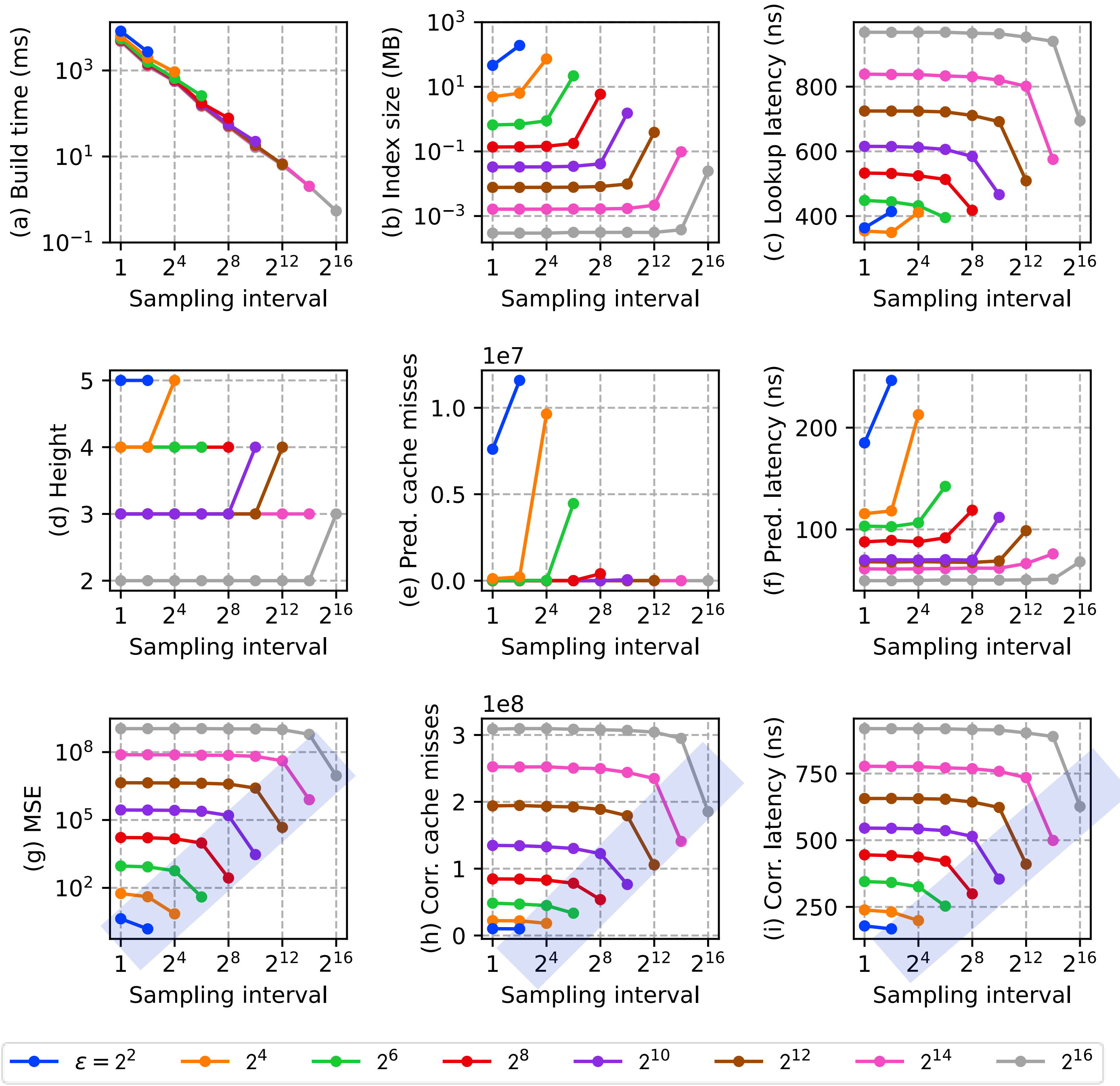
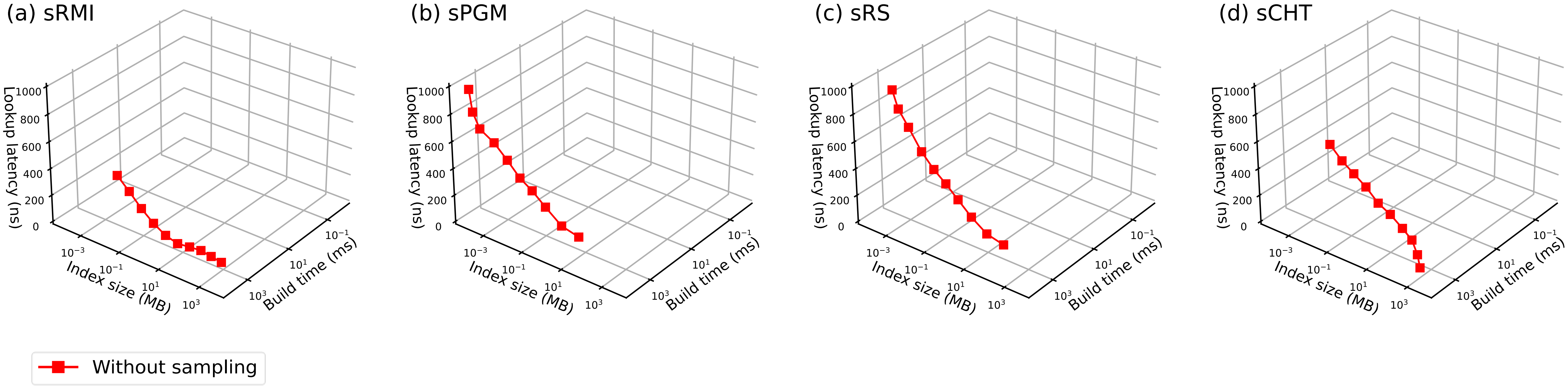


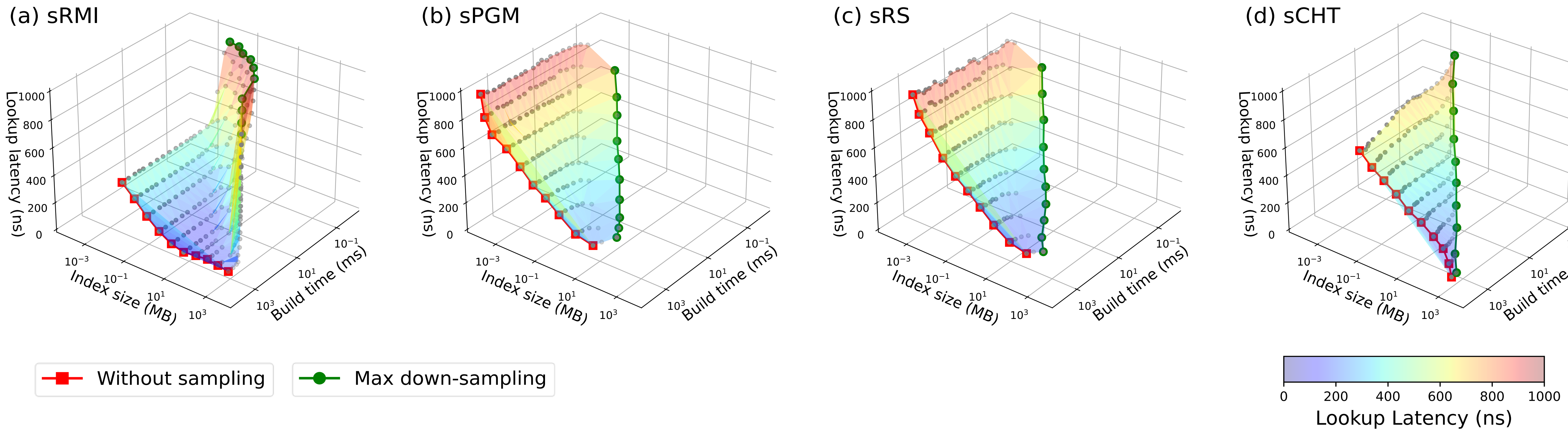
5. Evaluation

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



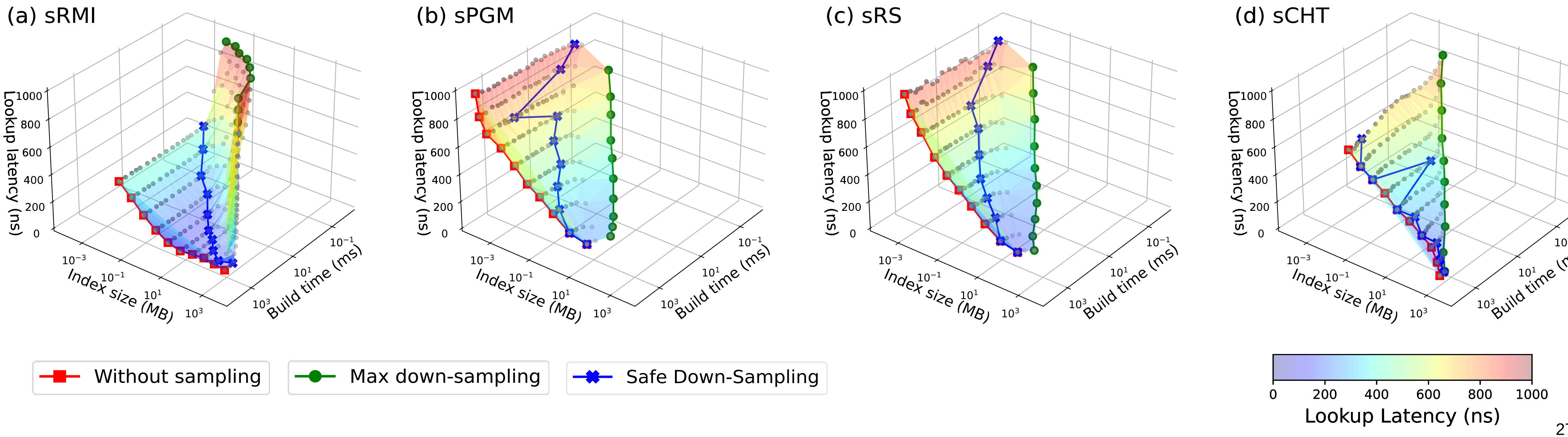
5. Evaluation

- 2. Design Space of Learned Indexes
  - Sampling **introduces** trade-offs between build-time, size, and lookup latency
    - Broaden 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 & lookup latency increase by less than 5%



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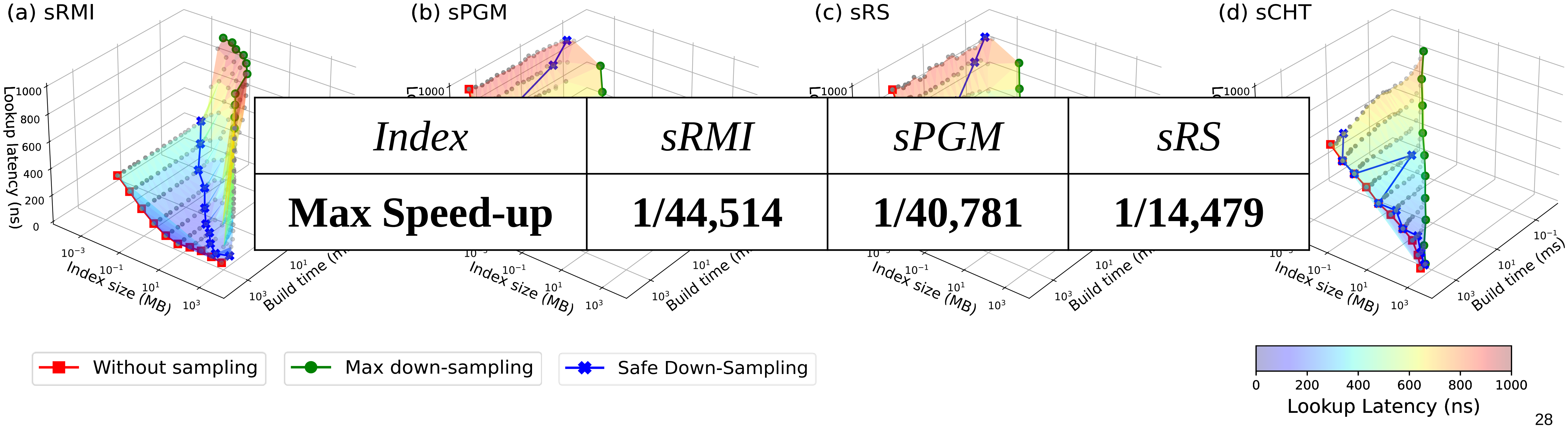
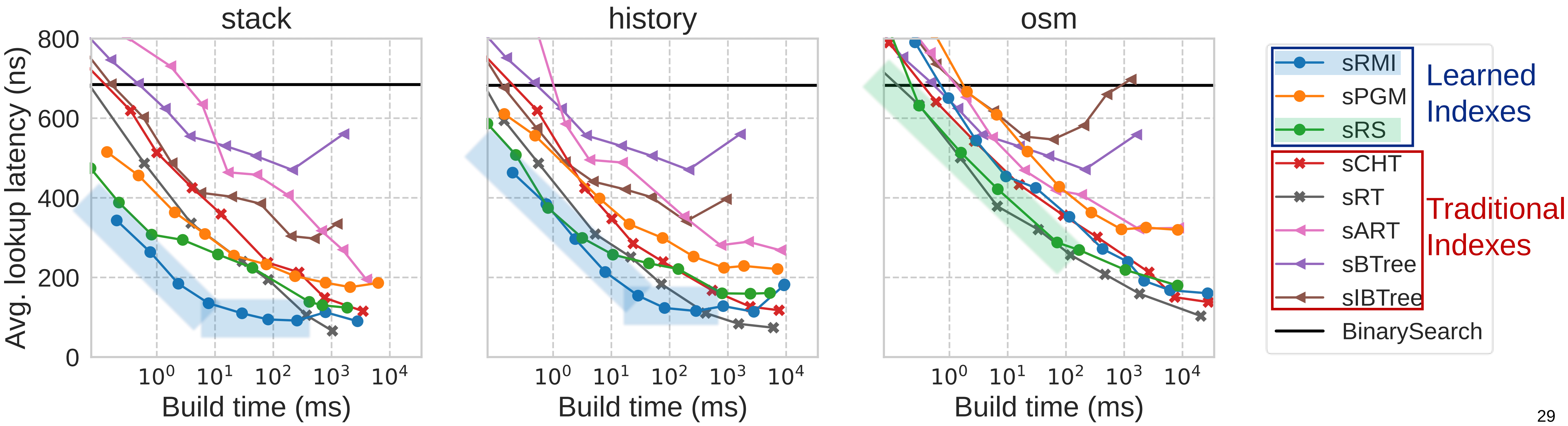


Index	*sRMI*	*sPGM*	*sRS*
Max Speed-up	**1/44,514**	**1/40,781**	**1/14,479**

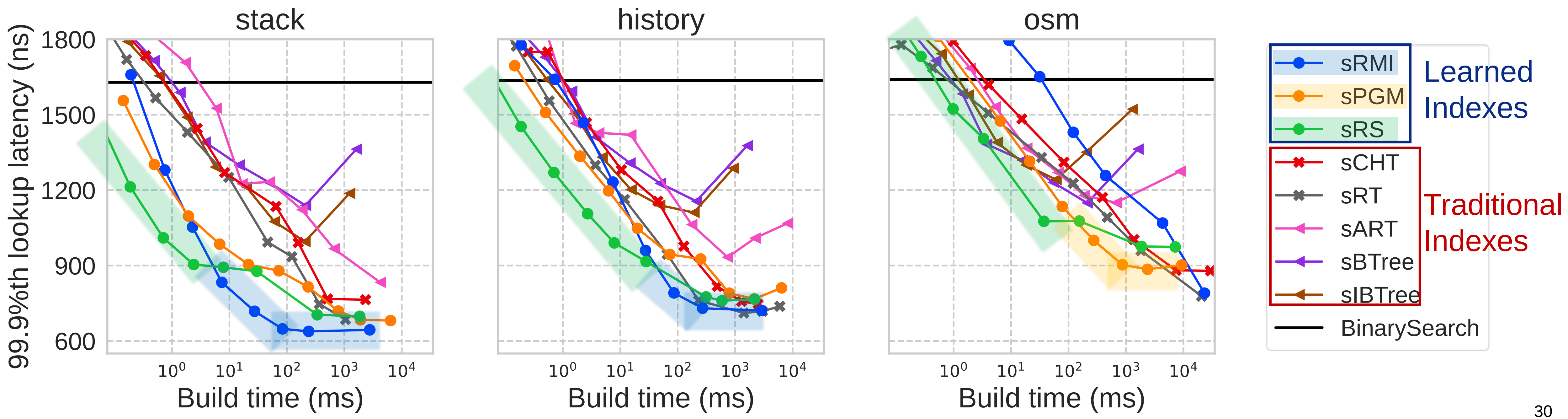
5. Evaluation

- 4. Pareto Optimal Analysis
  - Question. Can learned indexes be built efficiently (in terms of build time and lookup latency than traditional indexes 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 latency



5. Evaluation

- 4. Pareto Optimal Analysis
  - Question. Can learned indexes be built efficiently (in terms of build time and lookup latency than traditional indexes 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 latency



6. Conclusion

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

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

3. We propose 1) novel sample learning algorithms which preserves error-bound , 2) new benchmark BASIL, and 3) 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