FILM: a Fully Learned Index for Larger-than-Memory Databases

Ma, Chaohong, et al. VLDB 2022

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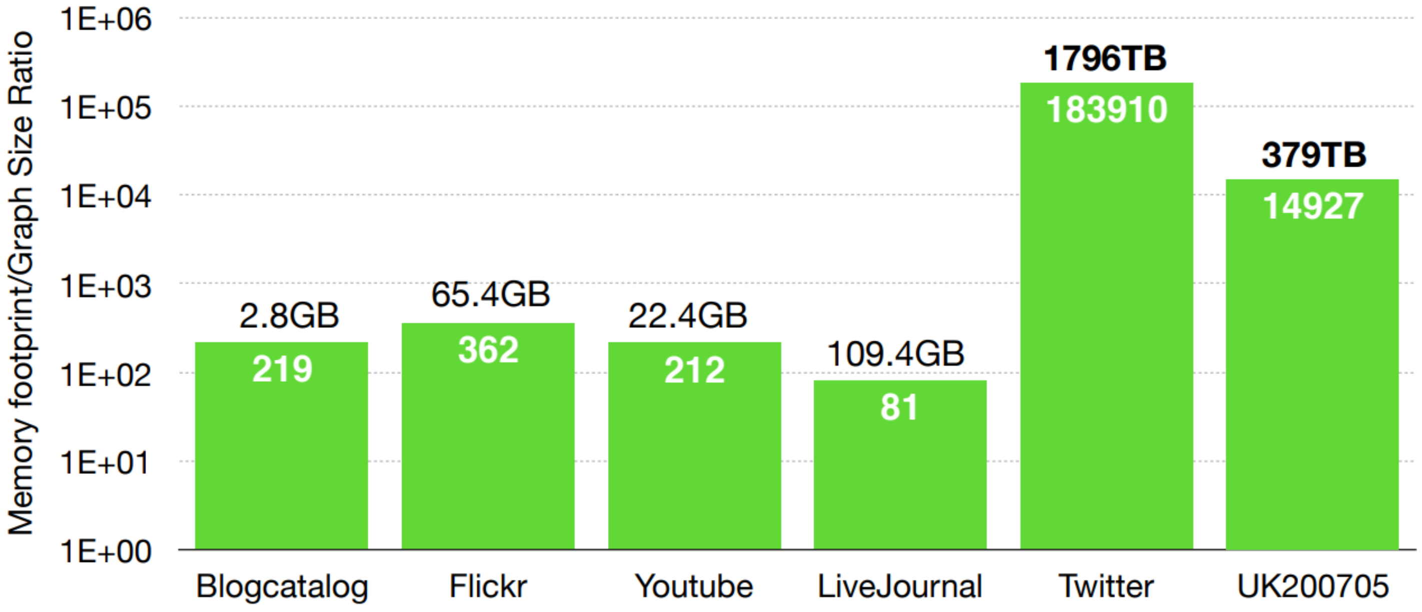
Introduction

- Data characteristics
  - Large volume and high velocity
  - Append-only
  - Diverse workloads



Reference: Shao, Yingxia, et al. "Memory-aware framework for fast and scalable second-order random walk over billion-edge natural graphs." *The VLDB Journal* 30.5 (2021)

Introduction

- Challenge

1) Existing index has **high disk I/O**

2) Existing index occupies **a large portion of memory**

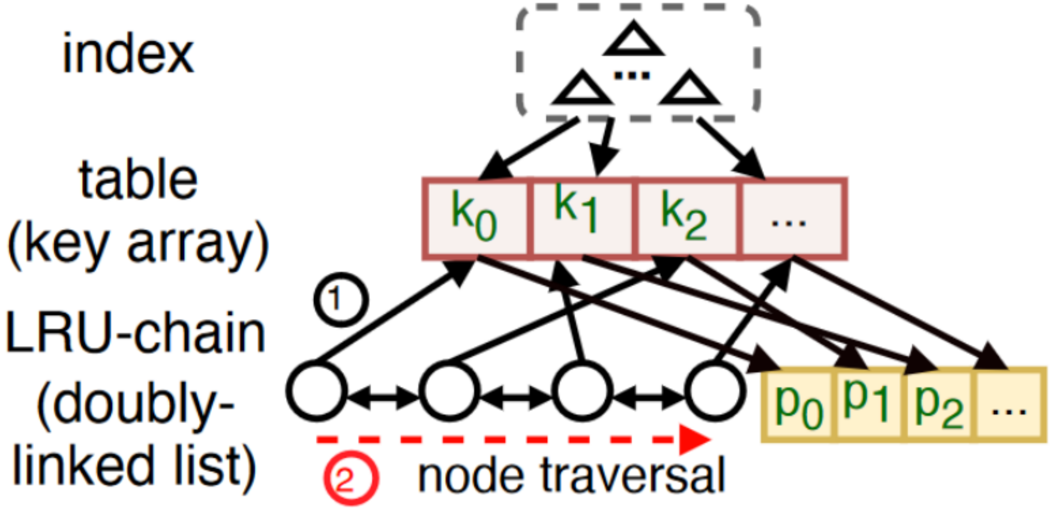
3) In ‘anti-caching’, computation **overhead in LRU is too high**

4) Learned index assumes data is stored in **a contiguous array**

5) Learned index is **for in-memory** data

Introduction

- Anti-caching
  - To reduce the consumption of main memory
  - High memory consumption
  - High LRU maintenance costs



(a) anti-caching's LRU

Introduction

- Goal

  - Using Learned Indexes in Heterogeneous storage

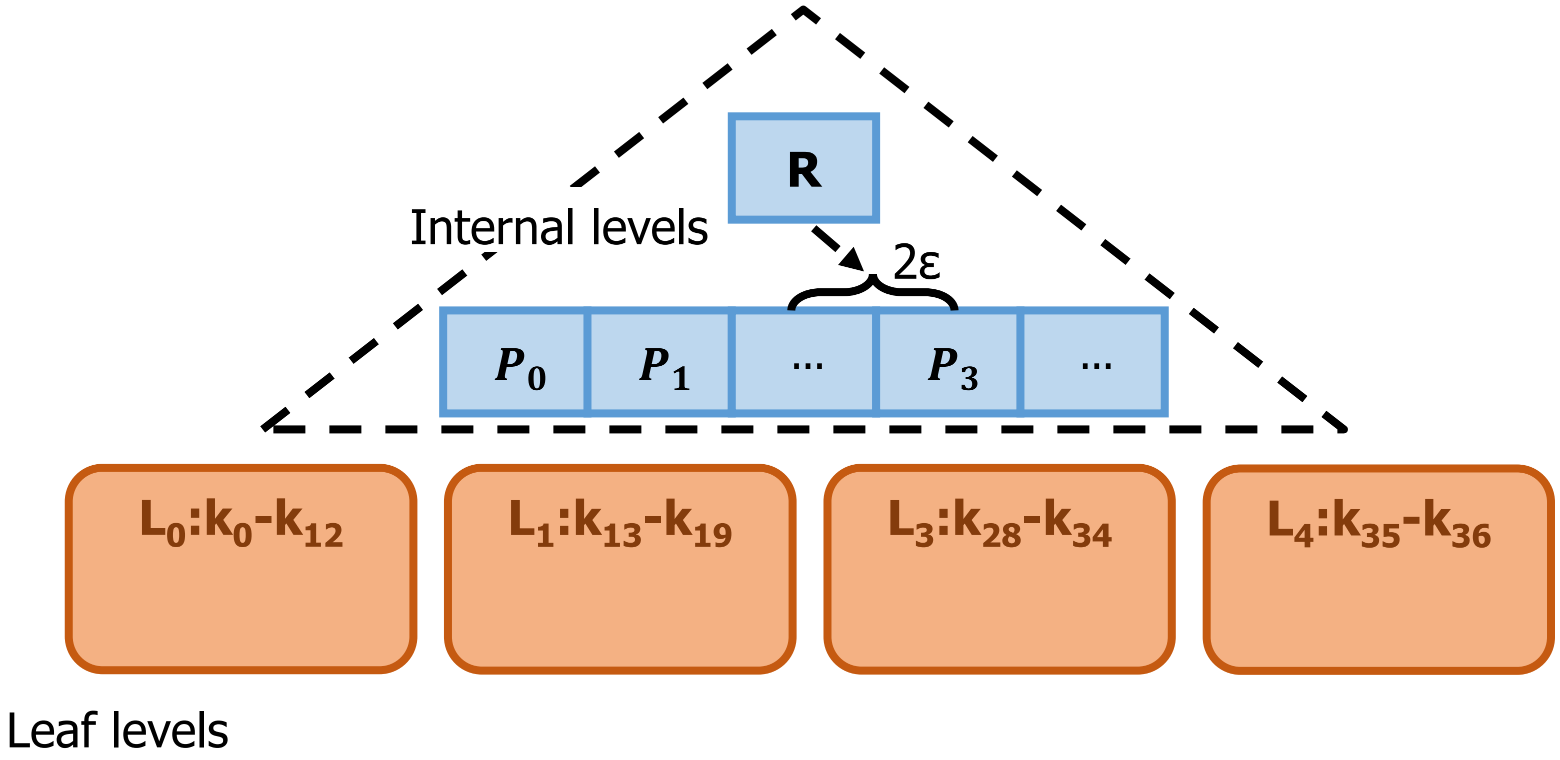
  - Cost Reduction of Cold Data Identification with Adaptive LRU

Design

1. **Lightweight Machine learning model**
   - Capturing data distribution to reduce memory usage
2. **Adaptive LRU**
   - Adaptive LRU for efficient cold data identification, cost-effective management
3. **Unified Tree Structure**
   - Stable tree structure minimizes maintenance despite data swapping

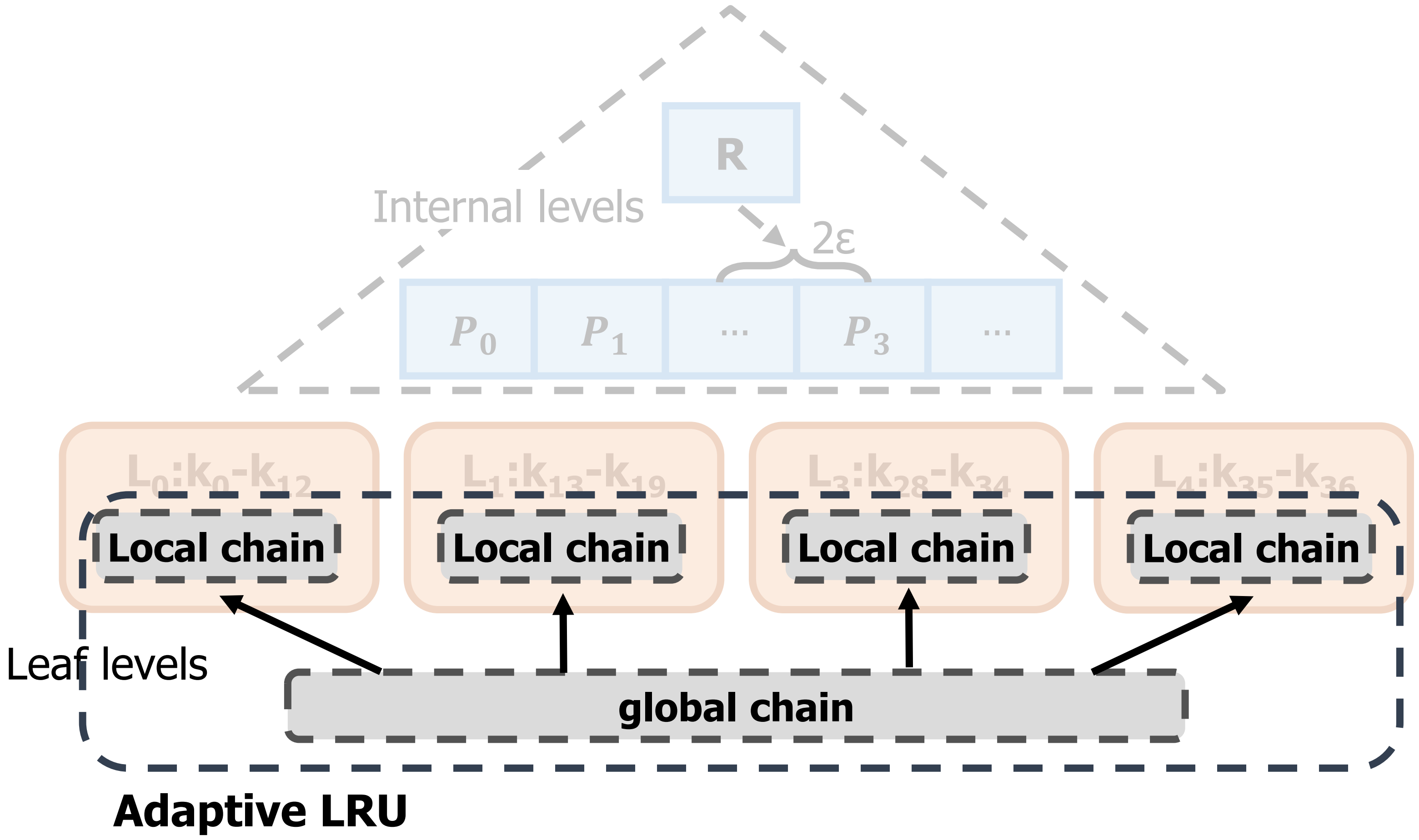
Design

- **Learned index**
- adaptive LRU
- Unified tree structure



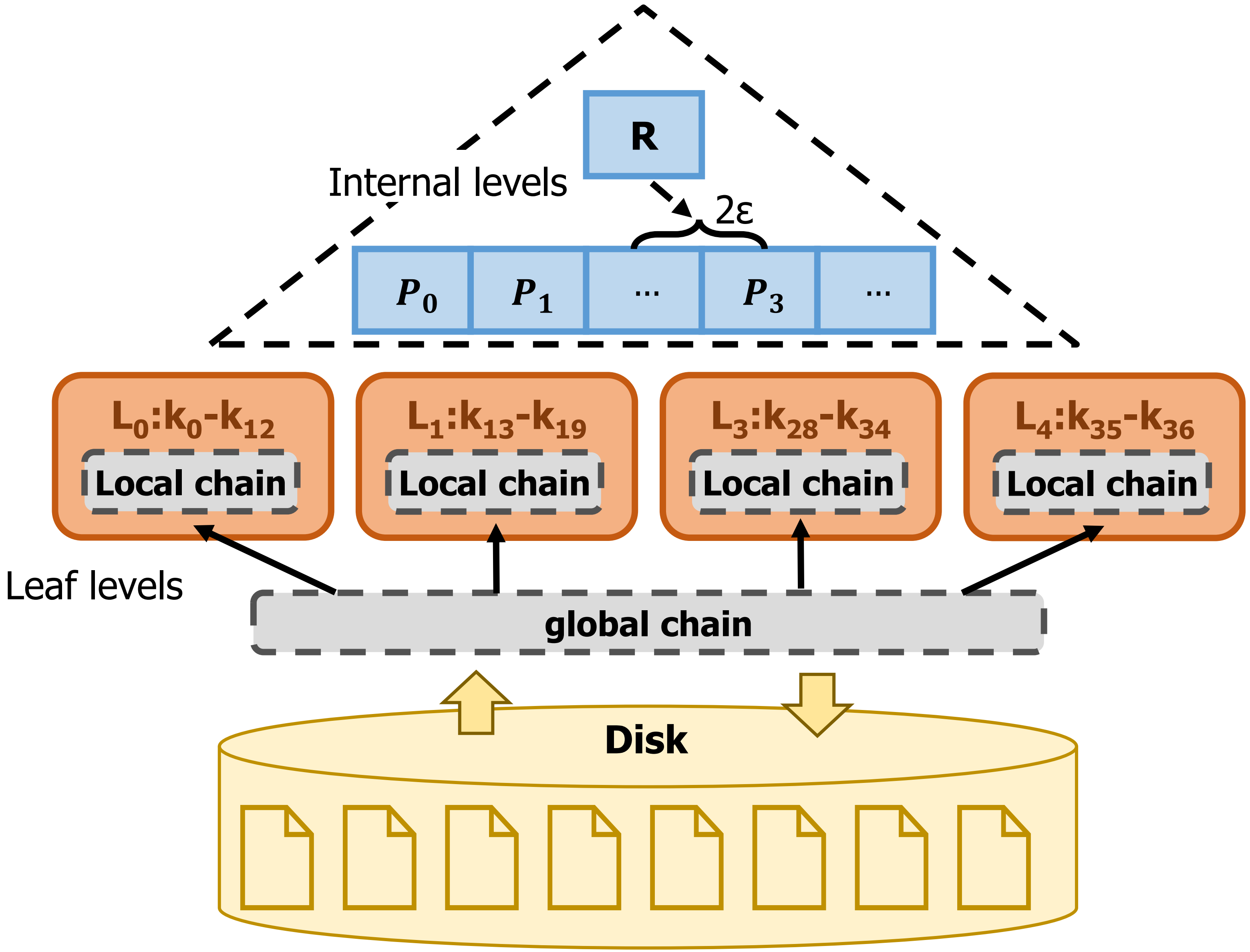
Design

- Learned index
- **adaptive LRU**
- Unified tree structure



Design

- Learned index
- adaptive LRU
- **Unified tree structure**



The Design of Piece

- Piece

  - Contains a sub-range of data and an approximation model fitted on the sub-range

  - Use a list of pwlfs (piecewise linear functions) to partition the sub-range of keys

  - The model guarantees the following formula (ε: a specified distance bound)

$$|pred\_pos - true\_pos| \leq \varepsilon$$

  - Newly inserted key breaking constraint is inserted into new piece,
    this key is called 'break_k'

The Design of Piece

i_piece

l_piece

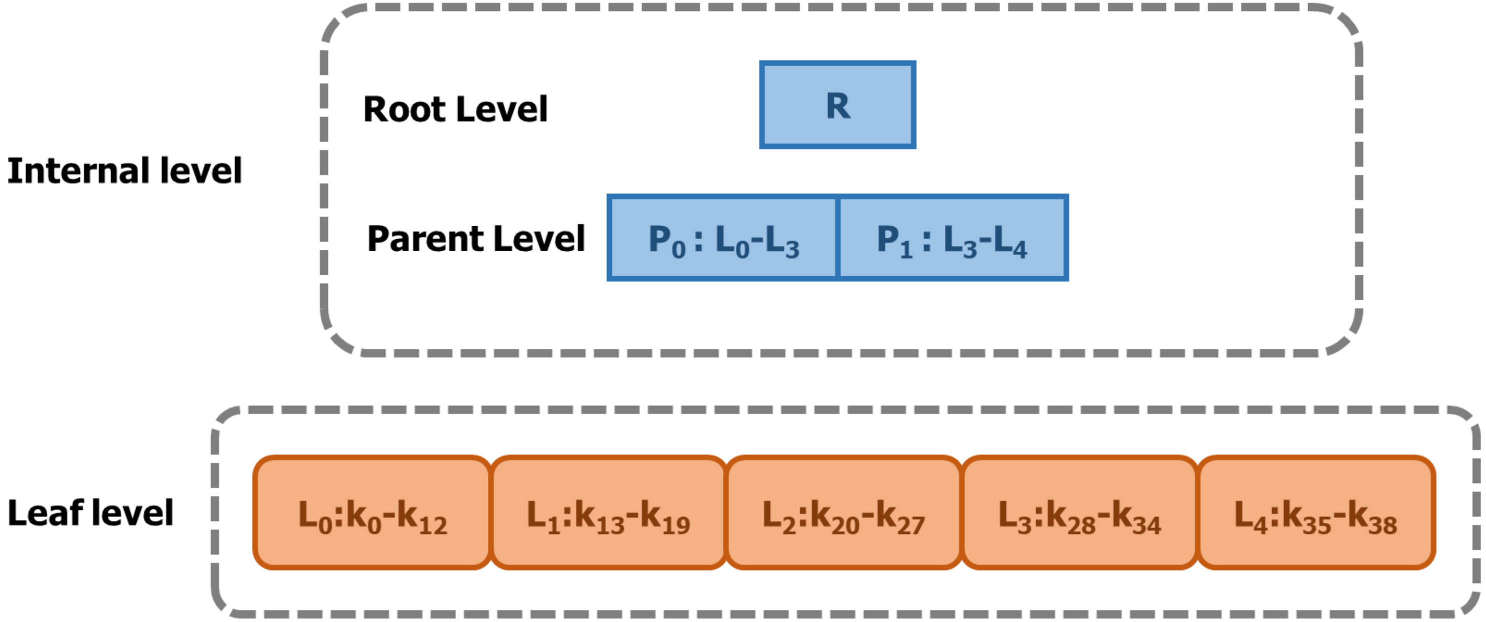
- Two types of piece
  - Component of pieces
  - Learned model with pieces

i_piece

- startK
- slope
- intercept

l_piece

- startK
- endK
- slope
- intercept
- …

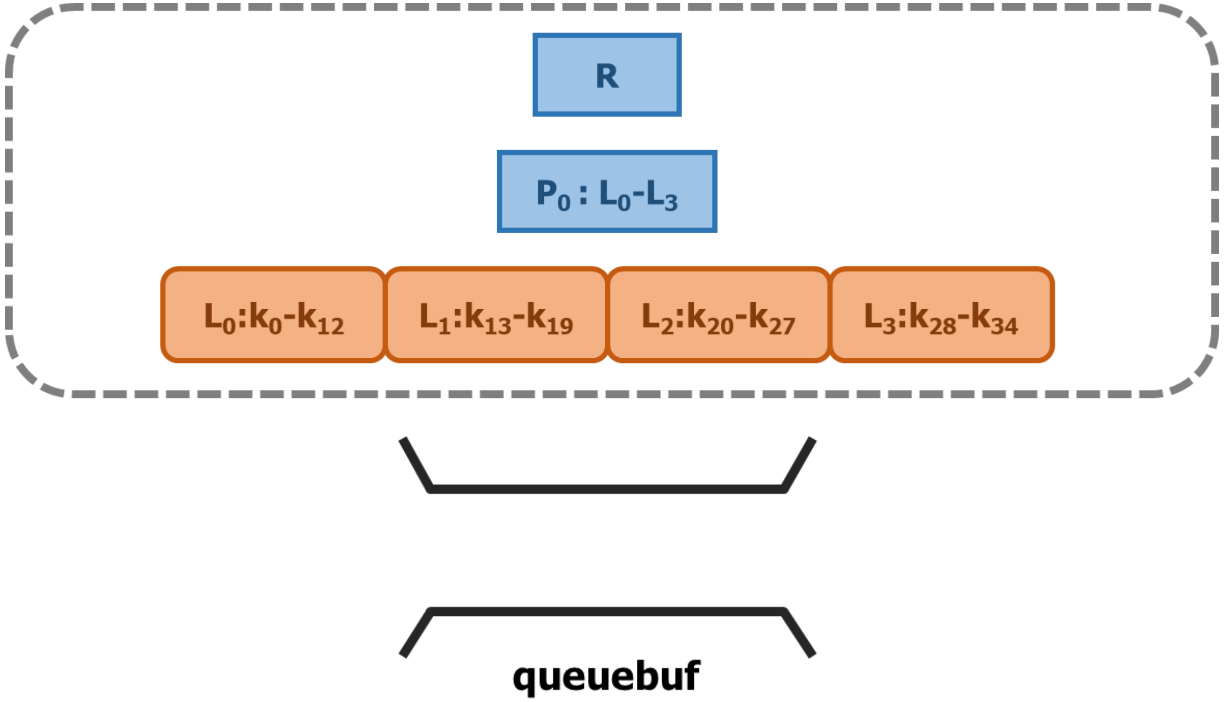


Dynamic Learned Model

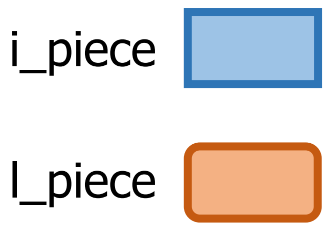
i_piece

l_piece

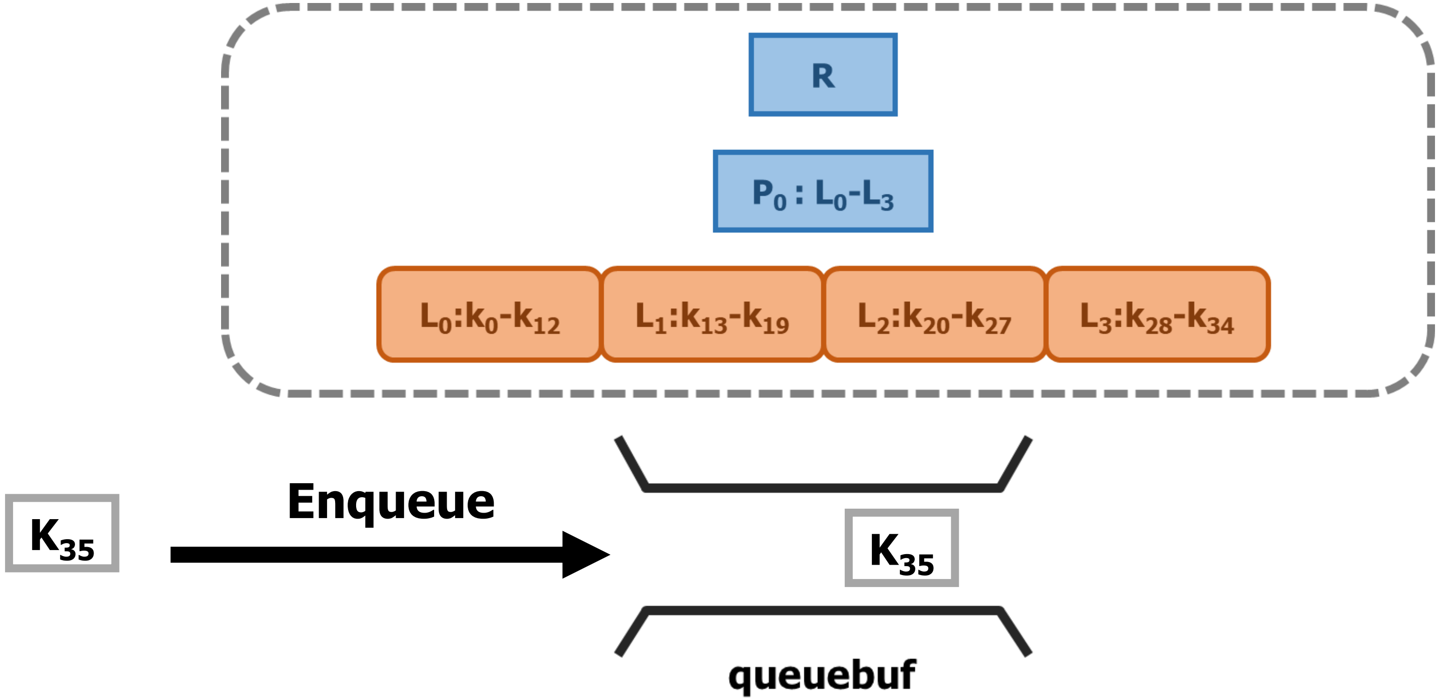
- The construction process of the learned model
  - Two break_k are needed to create l_piece
  - Queuebuf is designed to temporarily store the break_k



Dynamic Learned Model



- The construction process of the learned model
  - Put newly arrived key (break_k) into queuebuf
  - If Key is not break_k, directly put into l_piece

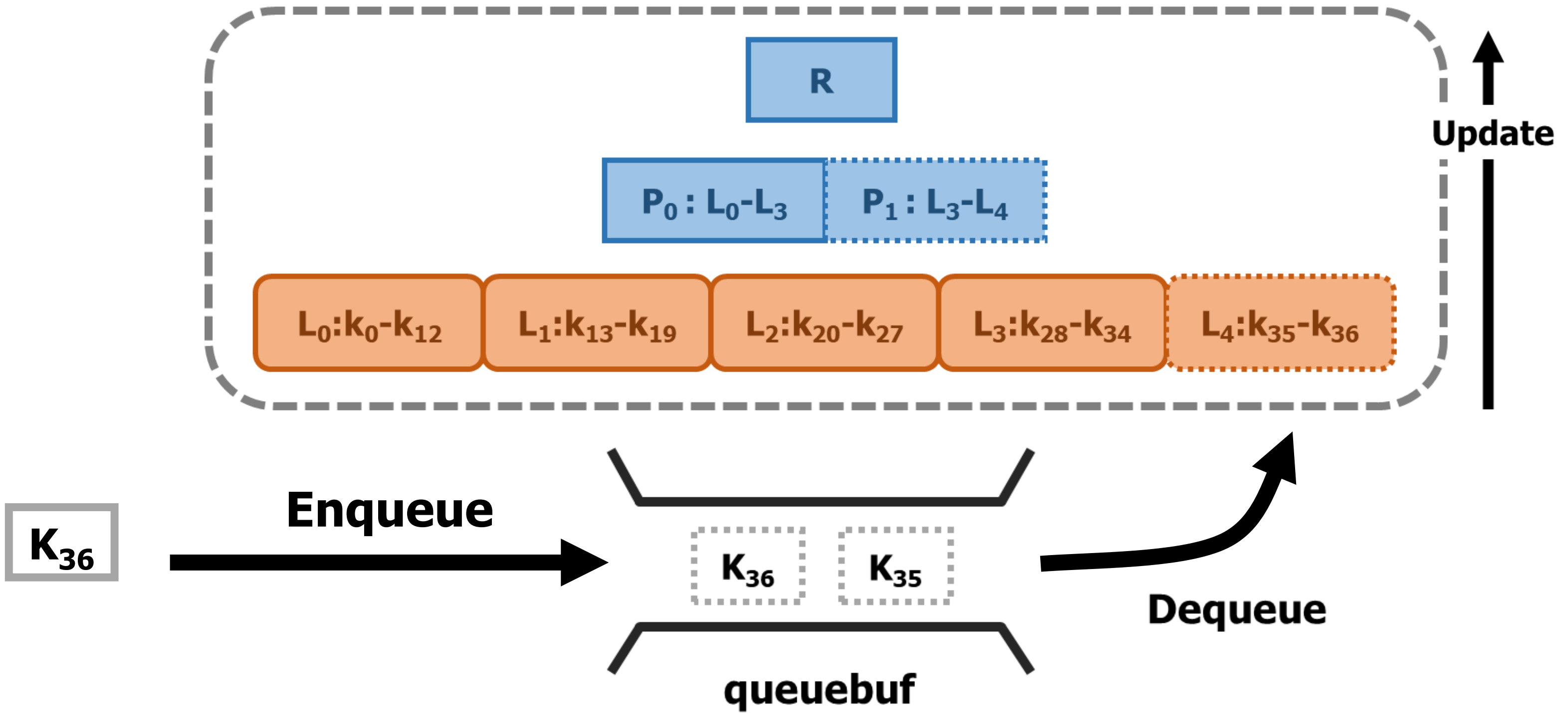


Dynamic Learned Model

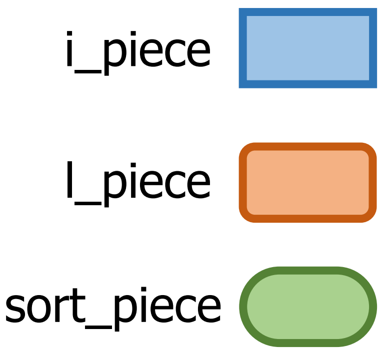
i_piece

l_piece

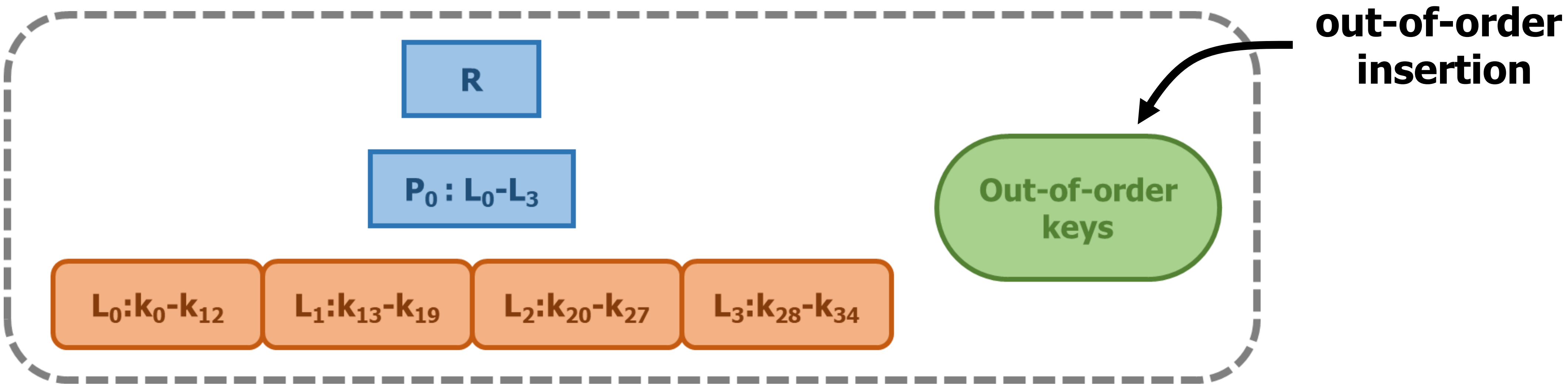
- The construction process of the learned model
  - Queuebuf is full, keys are removed and create a l_piece
  - Check if the parent level should be updated



Dynamic Learned Model

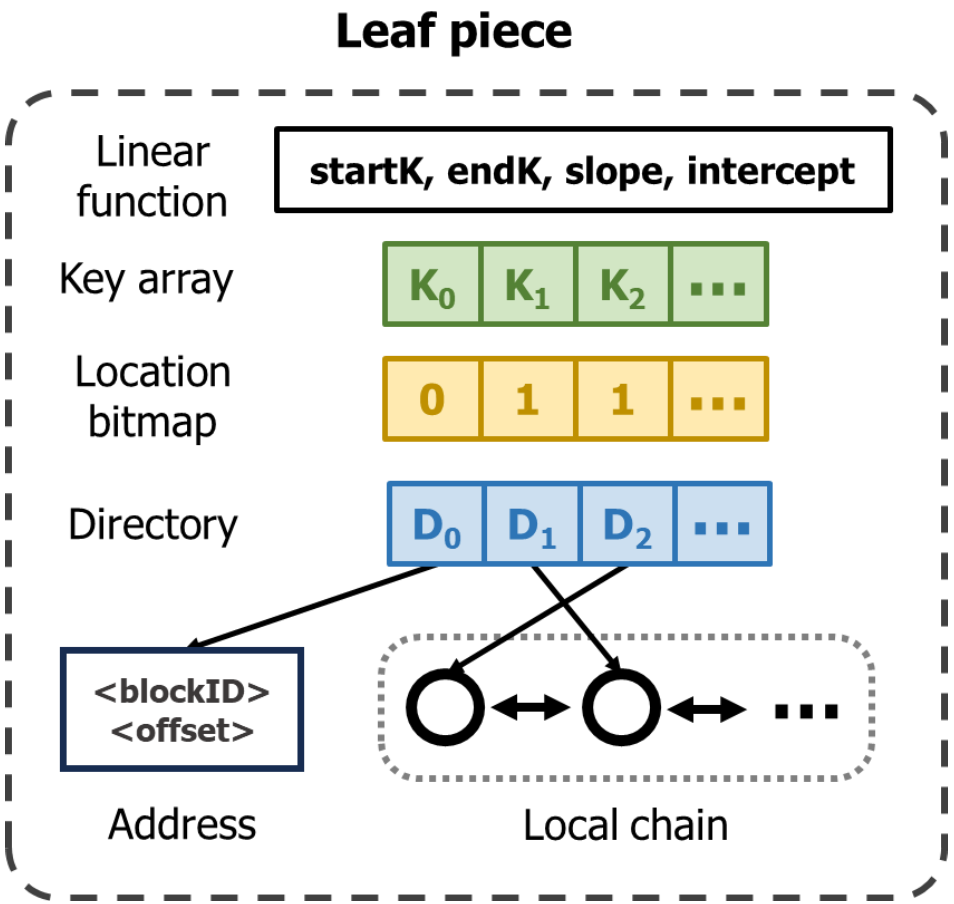


- Handling out-of-order insertions
  - Create sort_piece, which is special type of l_piece
  - Directly locates keys using binary search
  - Create a new l_piece when the size of sort_piece reaches the threshold



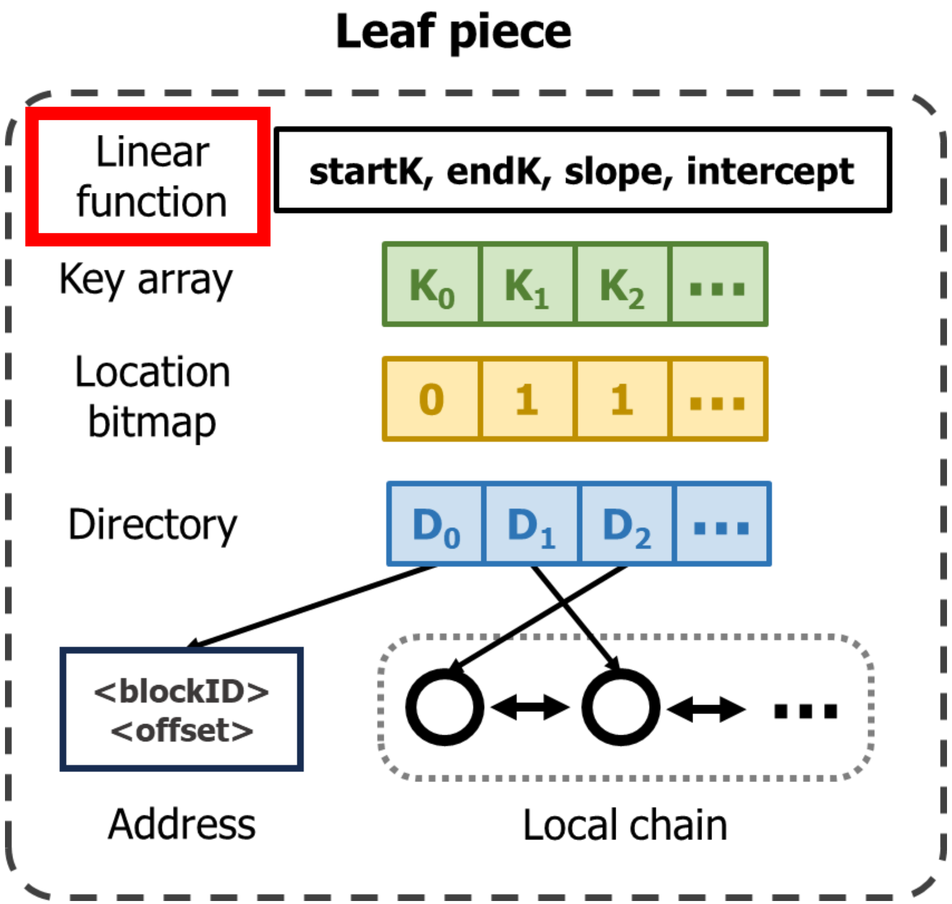
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
  - Key array
  - Location bitmap
  - Directory
  - Local chain
  - Address



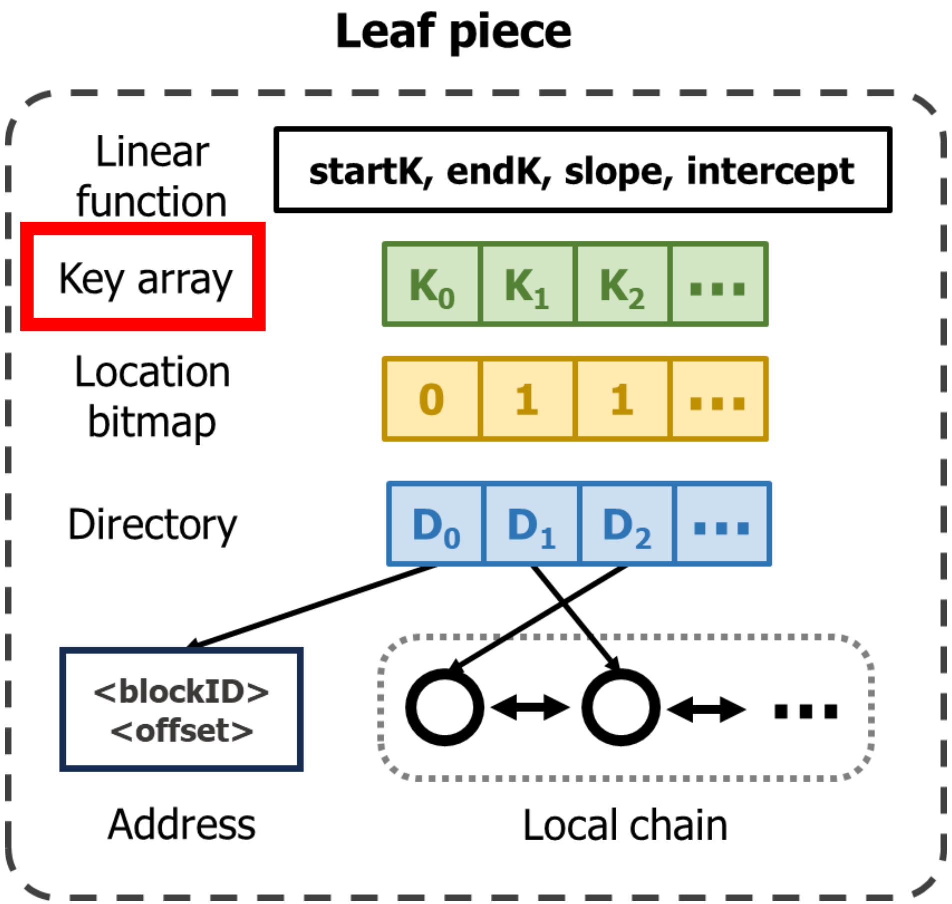
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
    - Predicting position of key
  - Key array
  - Location bitmap
  - Directory
  - Local chain
  - Address



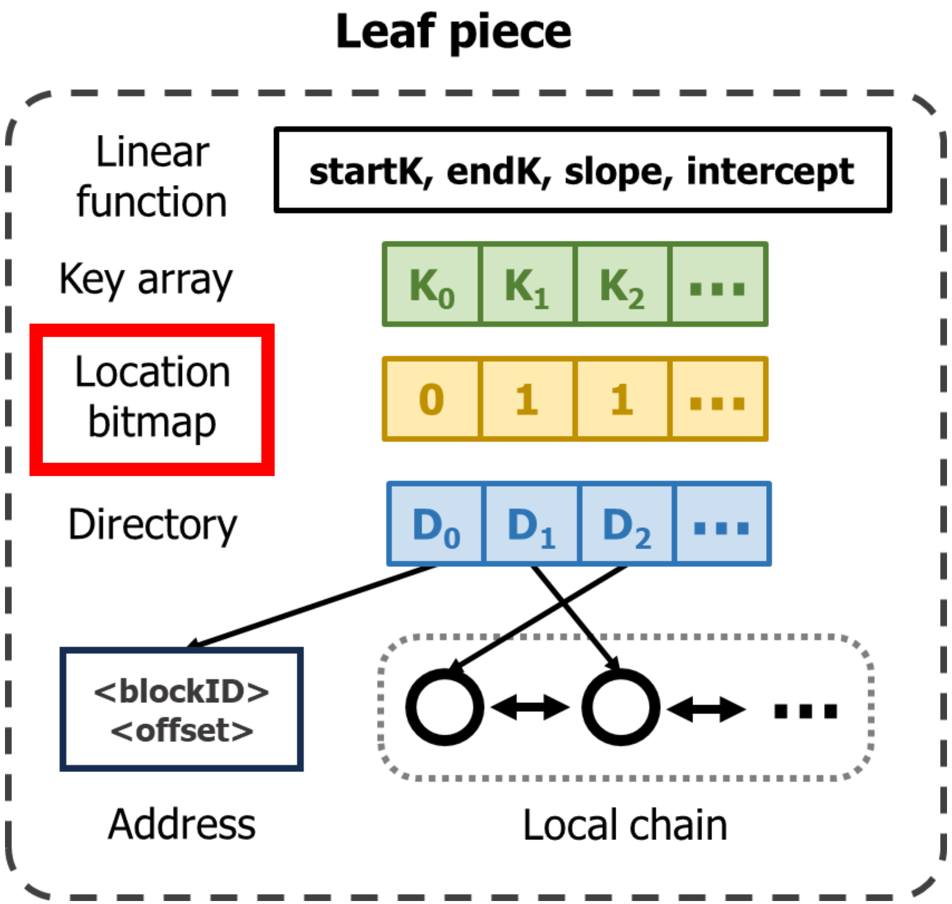
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
  - Key array
    - Recording the keys belonging to leaf piece
  - Location bitmap
  - Directory
  - Local chain
  - Address



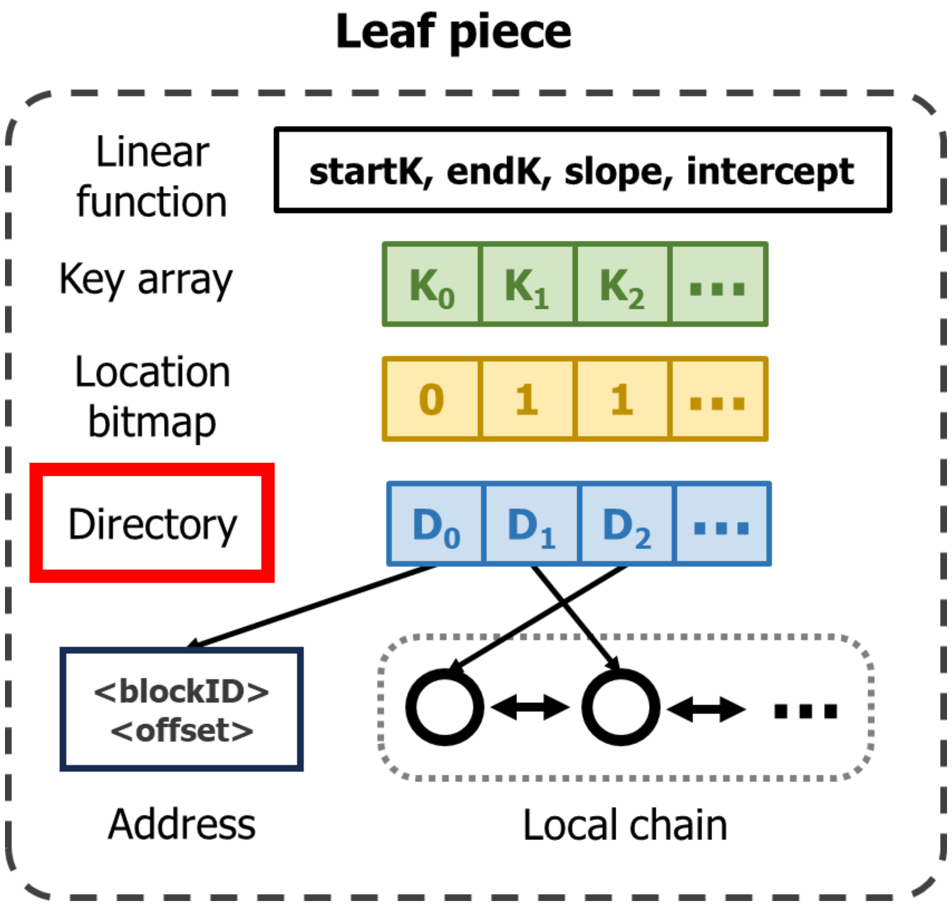
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
  - Key array
  - Location bitmap
    - Tracking whether corresponding data record is in memory or not
  - Directory
  - Local chain
  - Address



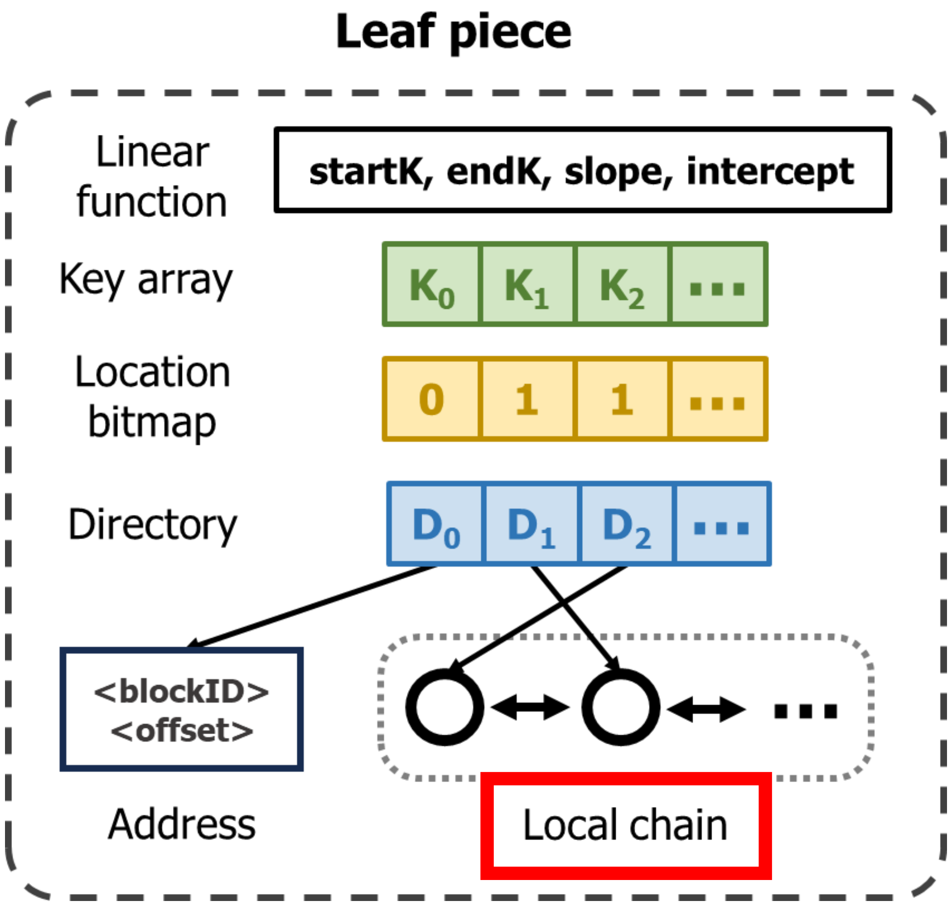
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
  - Key array
  - Location bitmap
  - Directory
    - Tracking the real position of all keys
  - Local chain
  - Address



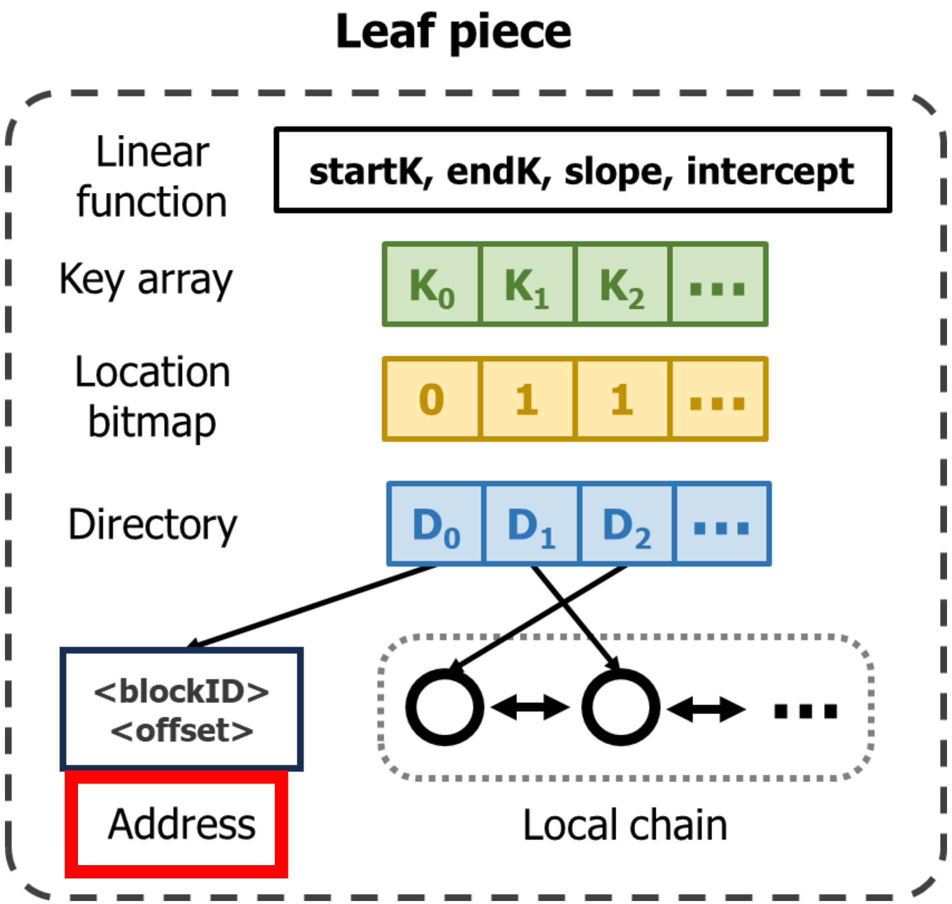
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
  - Key array
  - Location bitmap
  - Directory
  - Local chain
    - Maintain LRU order of keys
    - More details in next section
  - Address



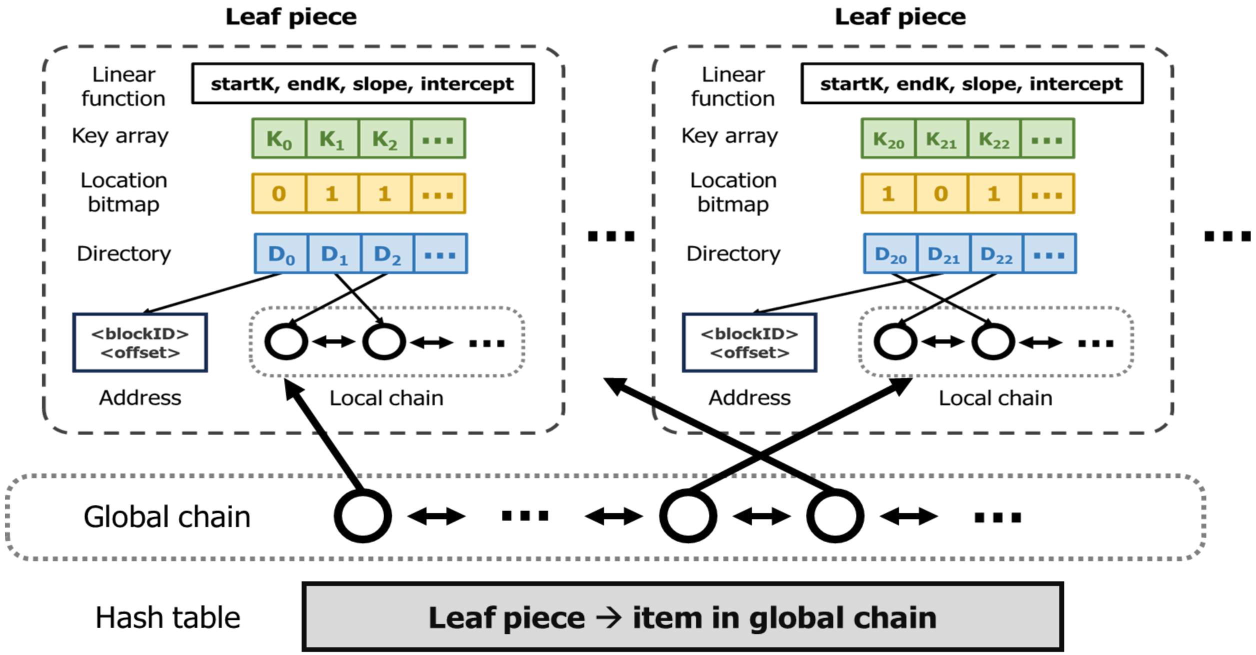
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
  - Key array
  - Location bitmap
  - Directory
  - Local chain
  - Address
    - Stores the addresses of all evicted records



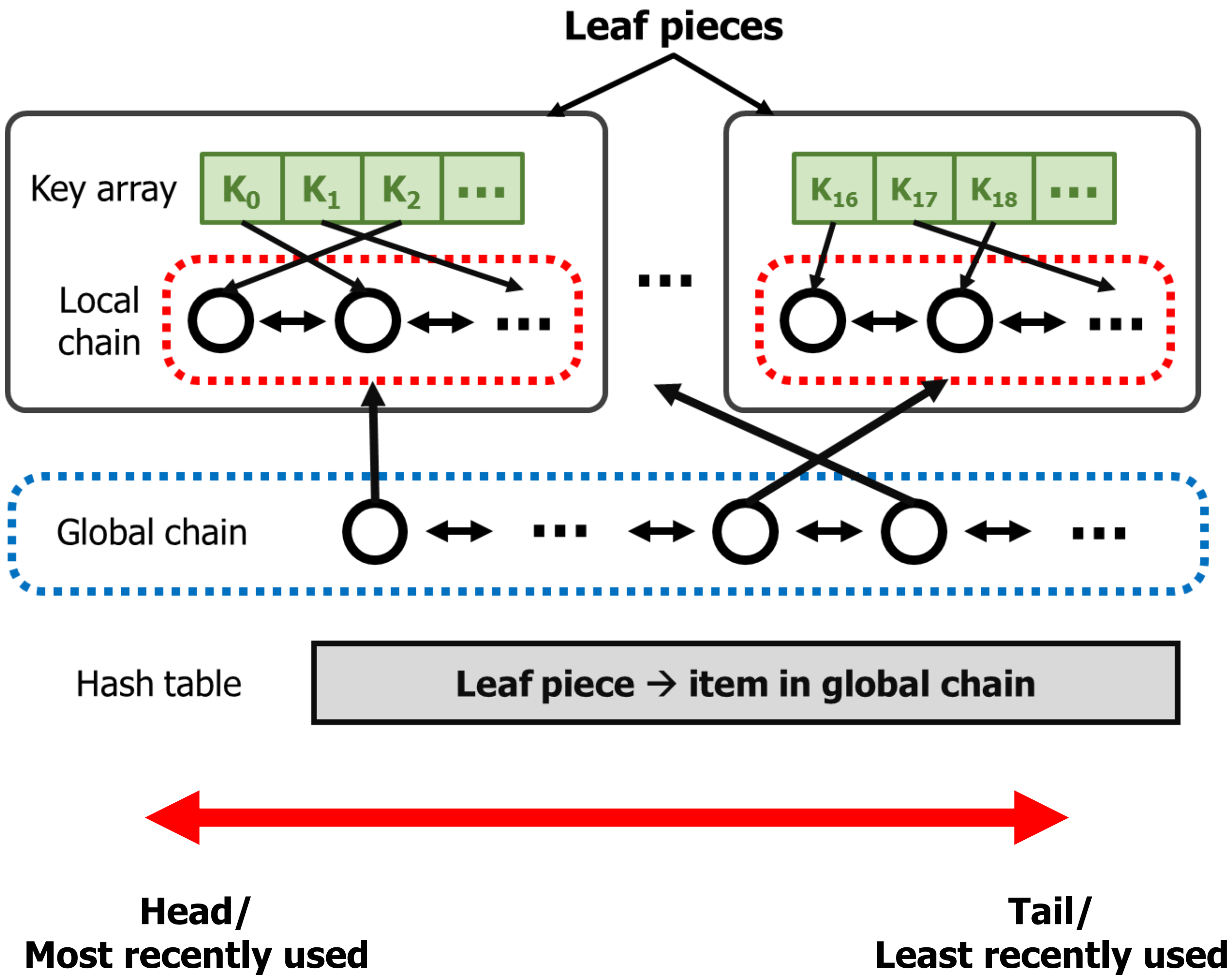
Dynamic Learned Model

- Leaf piece and adaptive LRU of FILM
  - FILM consists of local, global chain to support adaptive LRU
  - Reduce the overhead of maintaining the LRU chain by **piggybacking** the maintenance of the LRU order on the index lookup



Adaptive LRU

- Local chain
  - A component in a leaf piece
  - Maintain LRU order of the keys
  - Stores the payloads of the keys
- Global chain
  - Points to a leaf piece
  - Maintain LRU order of the l_pieces
  - Track the global data access order across pieces
- Hash table
  - For fast search of nodes in global chain



Adaptive LRU

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  - A component in a leaf piece
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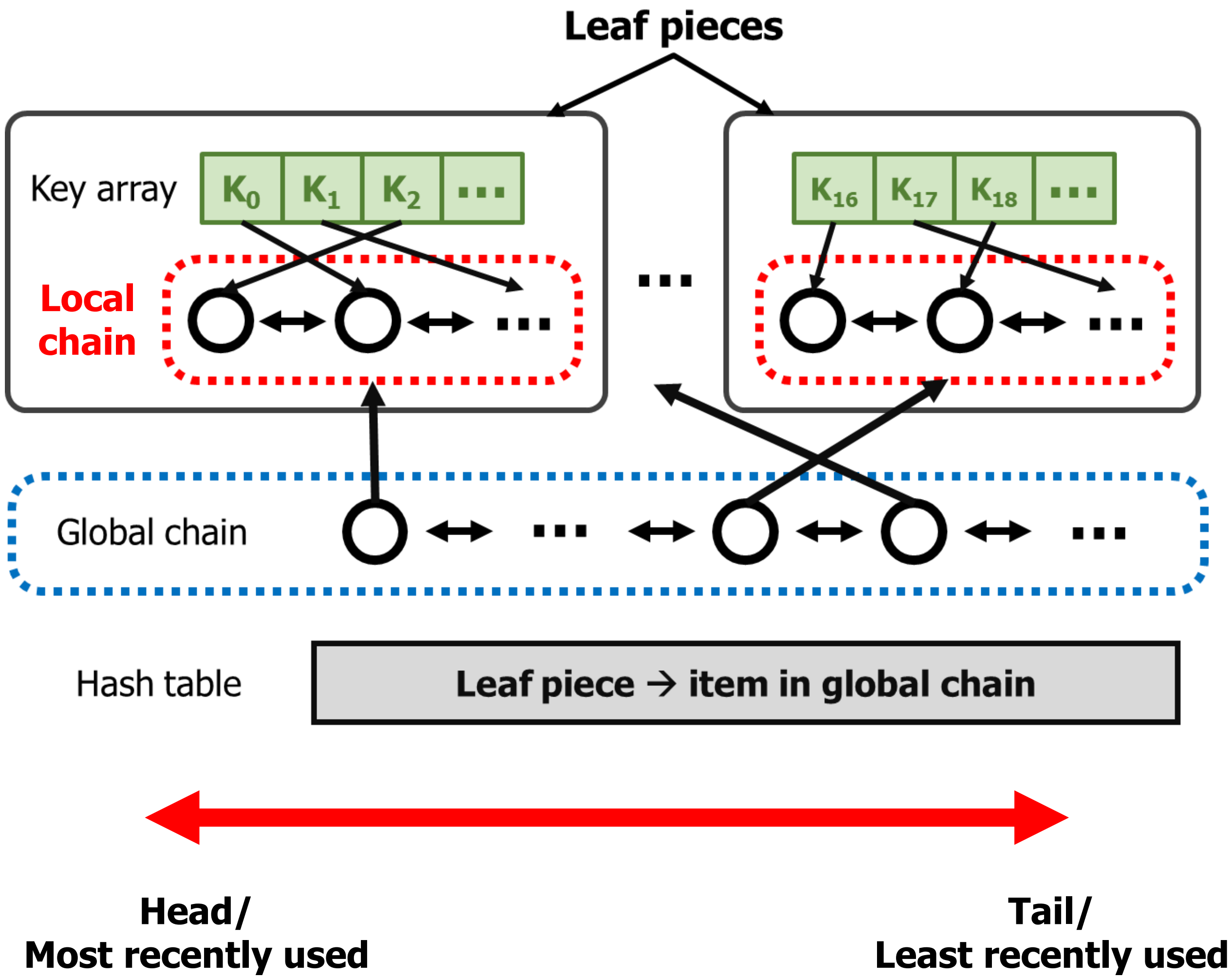

Adaptive LRU

- Local chain
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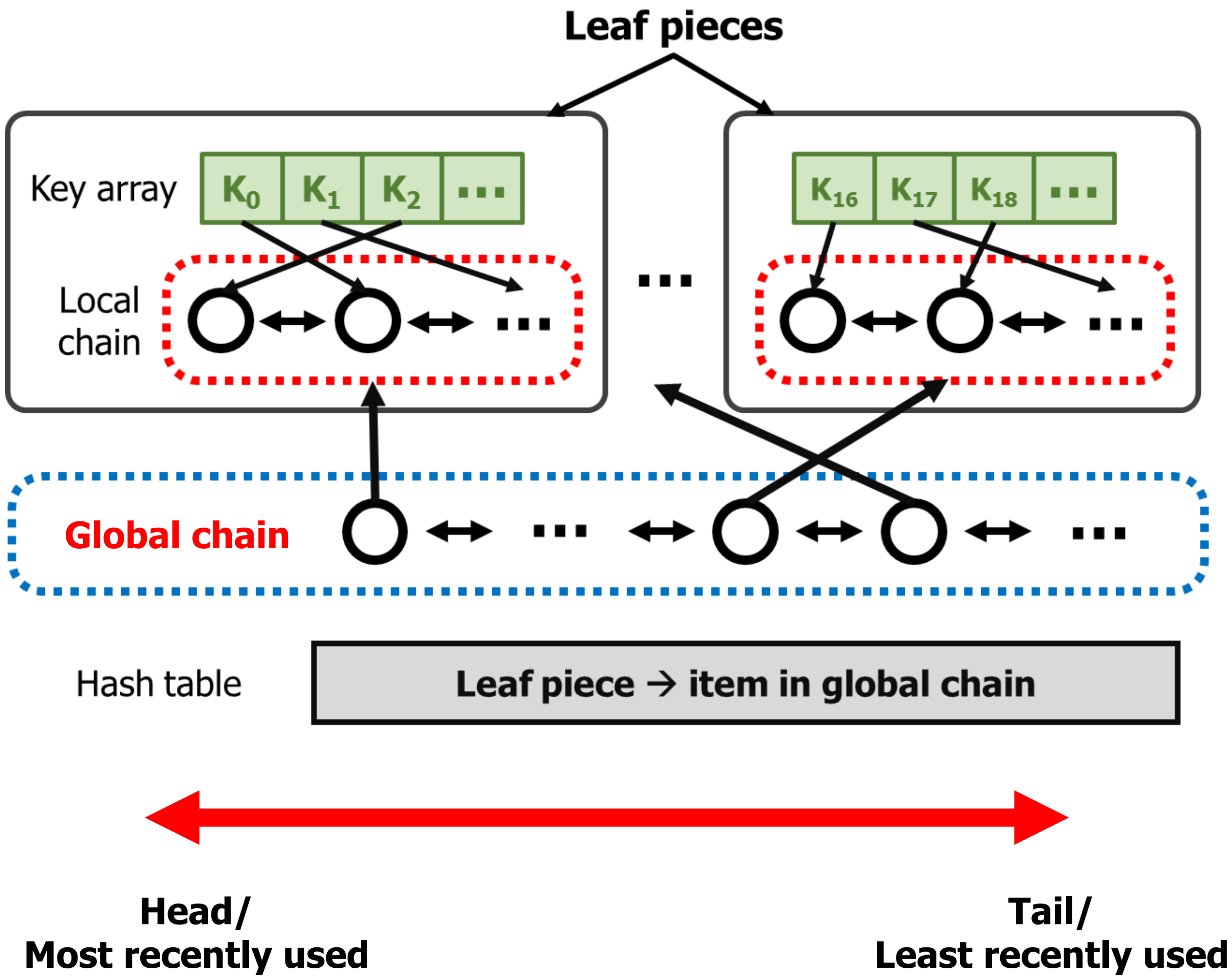
- **Global chain**
  - Points to a leaf piece
  - Maintain LRU order of the l_pieces
  - Track the global data access order across pieces

- Hash table
  - For fast search of nodes in global chain



Adaptive LRU

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  - A component in a leaf piece
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  - Stores the payloads of the keys

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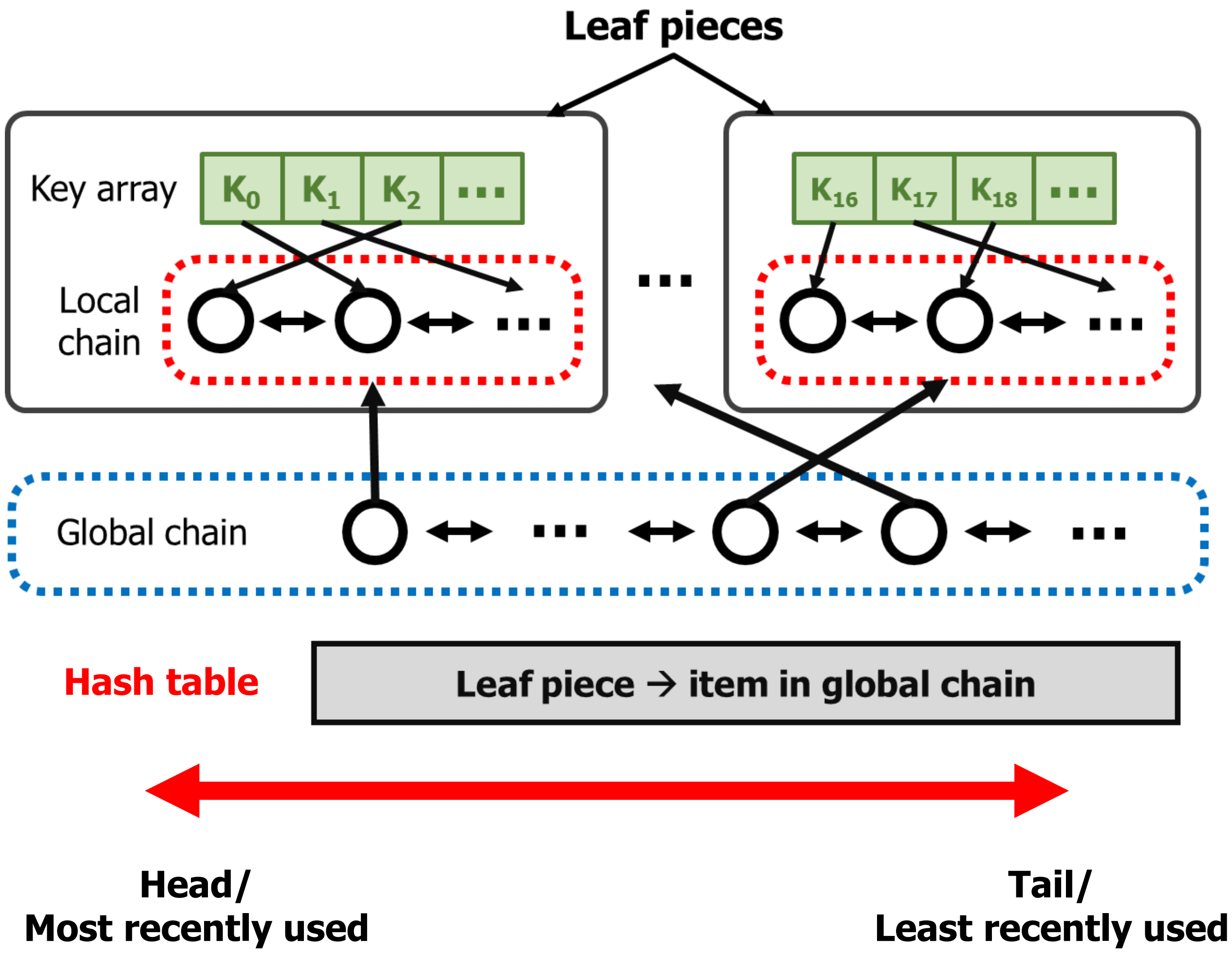
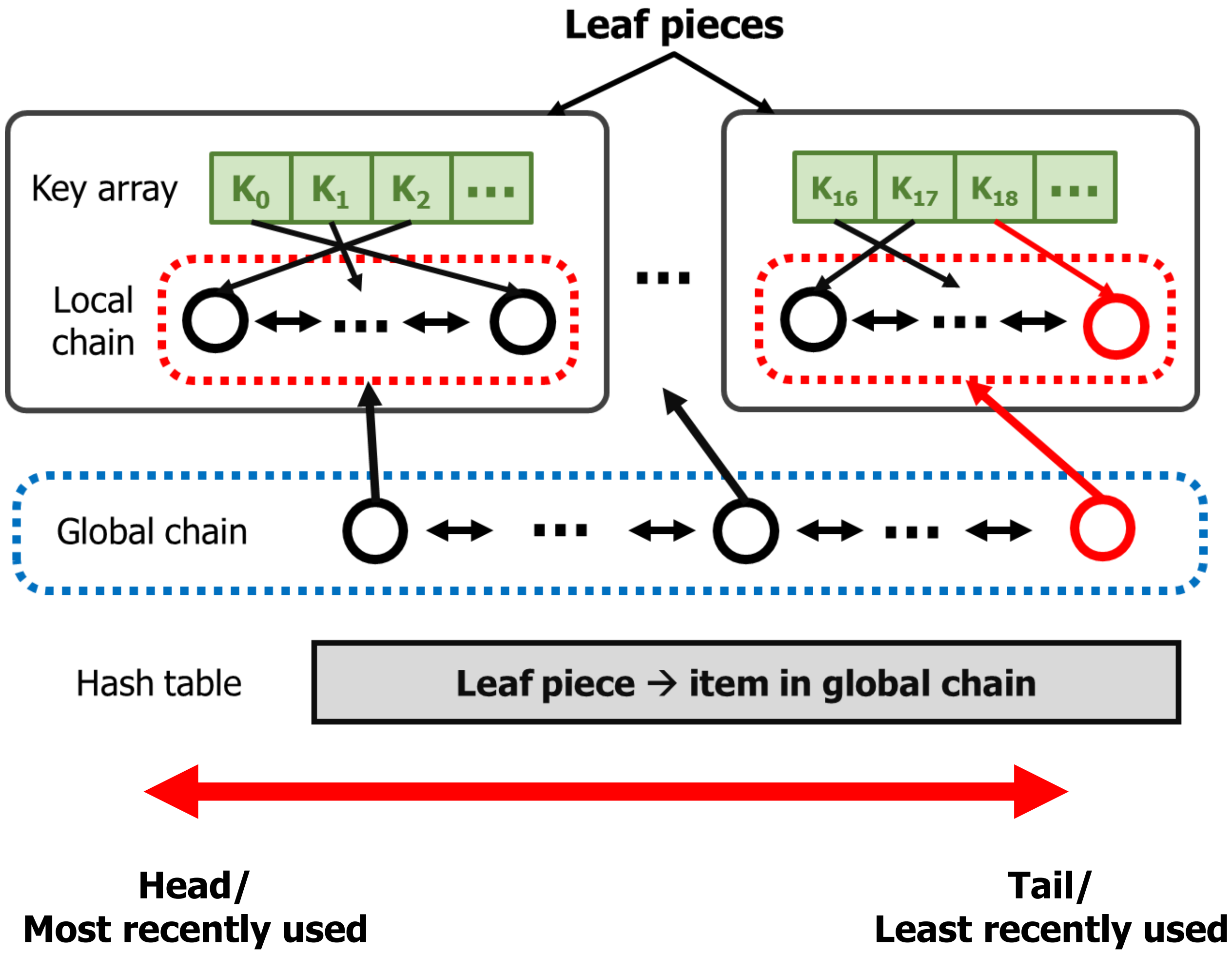
- **Hash table**
  - For fast search of nodes in global chain



Adaptive LRU

- Cold Data identification
  - When available memory runs out
    - Global chain identifies cold leaf piece to eviction
    - Evicts records from the coldest leaf to a block until block is full
  - Continue until database size reaches a user-specified threshold



Adaptive LRU

- Difference between FILM's adaptive LRU and anti-caching's LRU
  - FILM avoids the node traversal by piggybacking the locating of the LRU item onto the index lookup
  - An LRU item in FILM's adaptive LRU stores the payload of the corresponding record

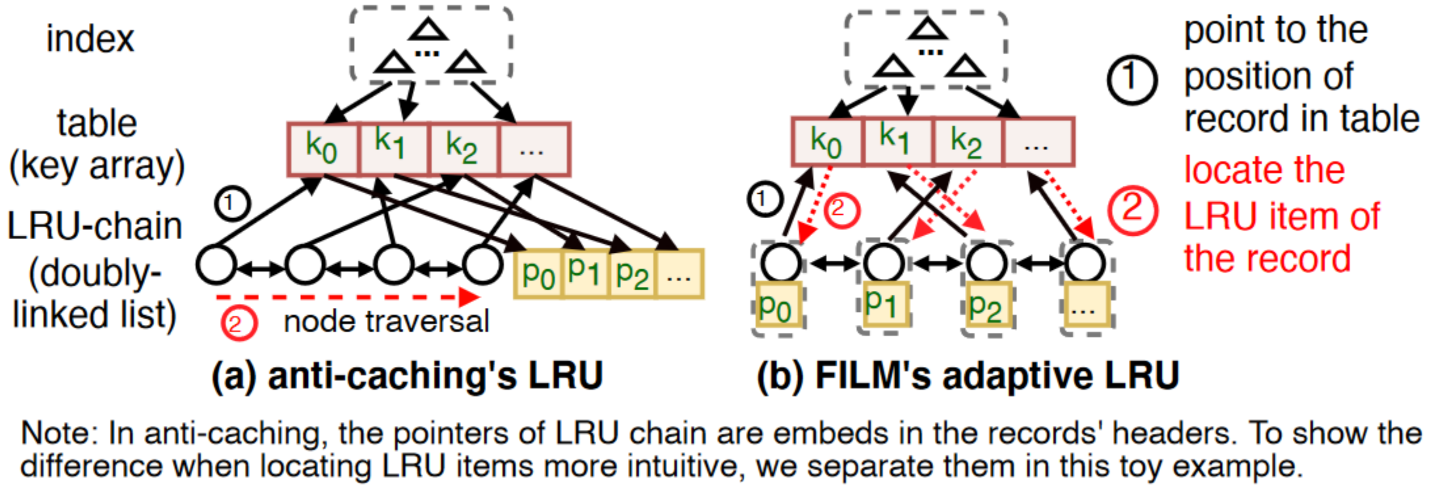


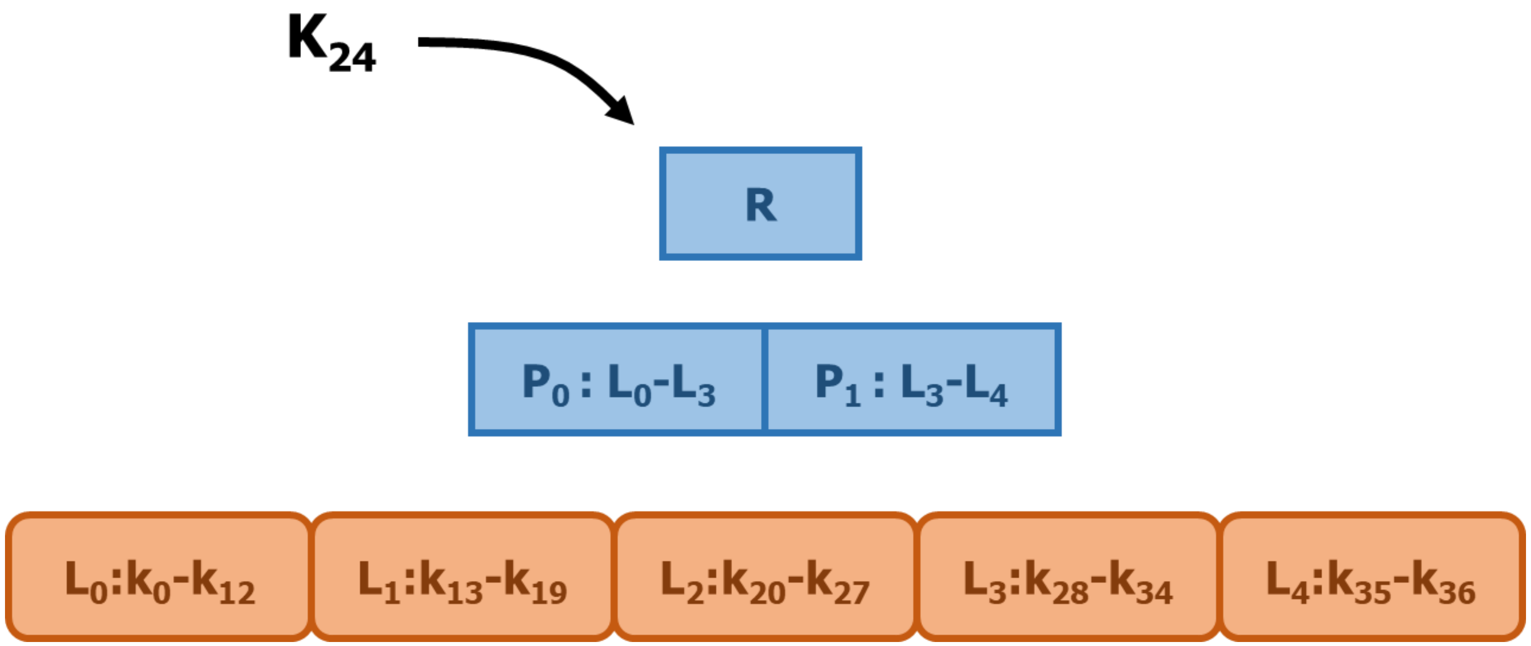
Fig. 4: LRU in anti-caching vs. adaptive LRU in FILM

Query Processing

- Point Query

1. Find the leaf piece that **K** belongs to

   Recursively predict the candidate pieces



Query Processing

- Point Query

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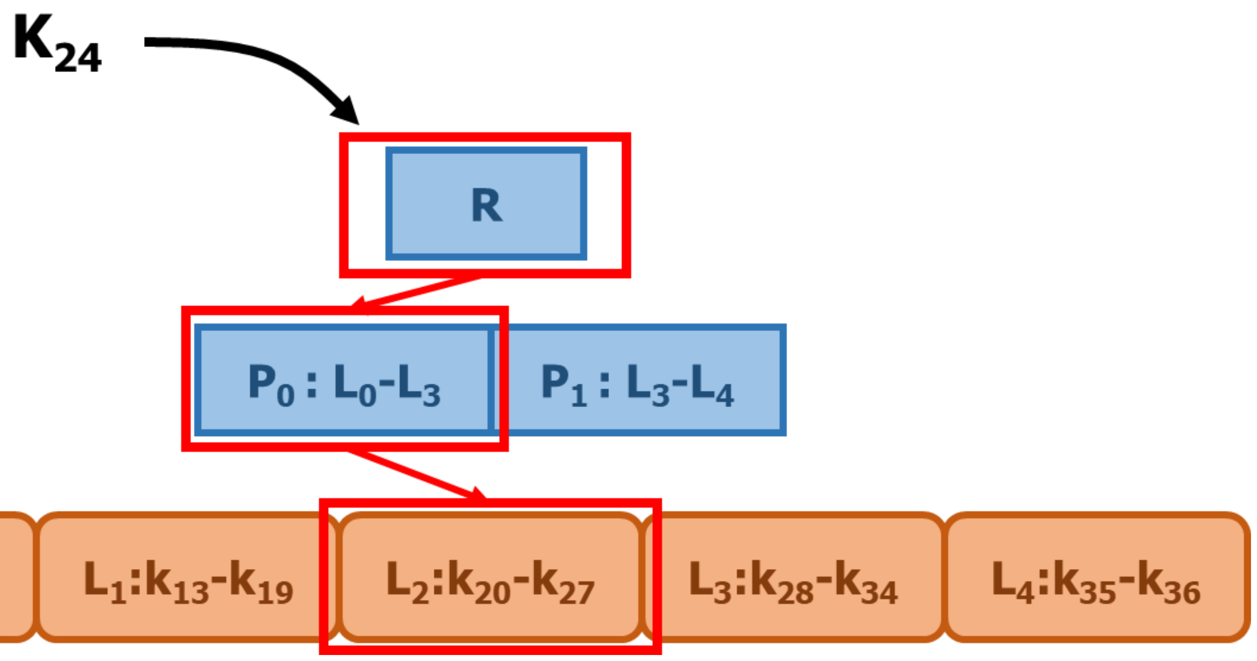
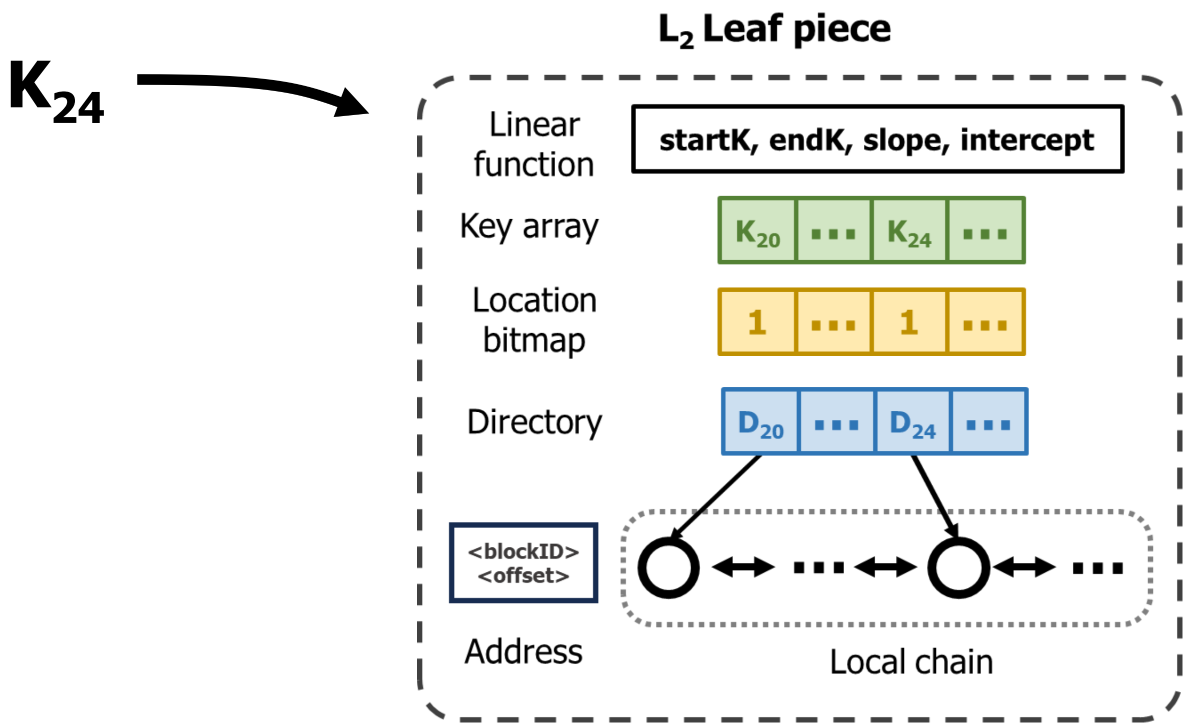


Query Processing

- Point Query

  2. Locate **K** in the piece

     Predict the position of **K**

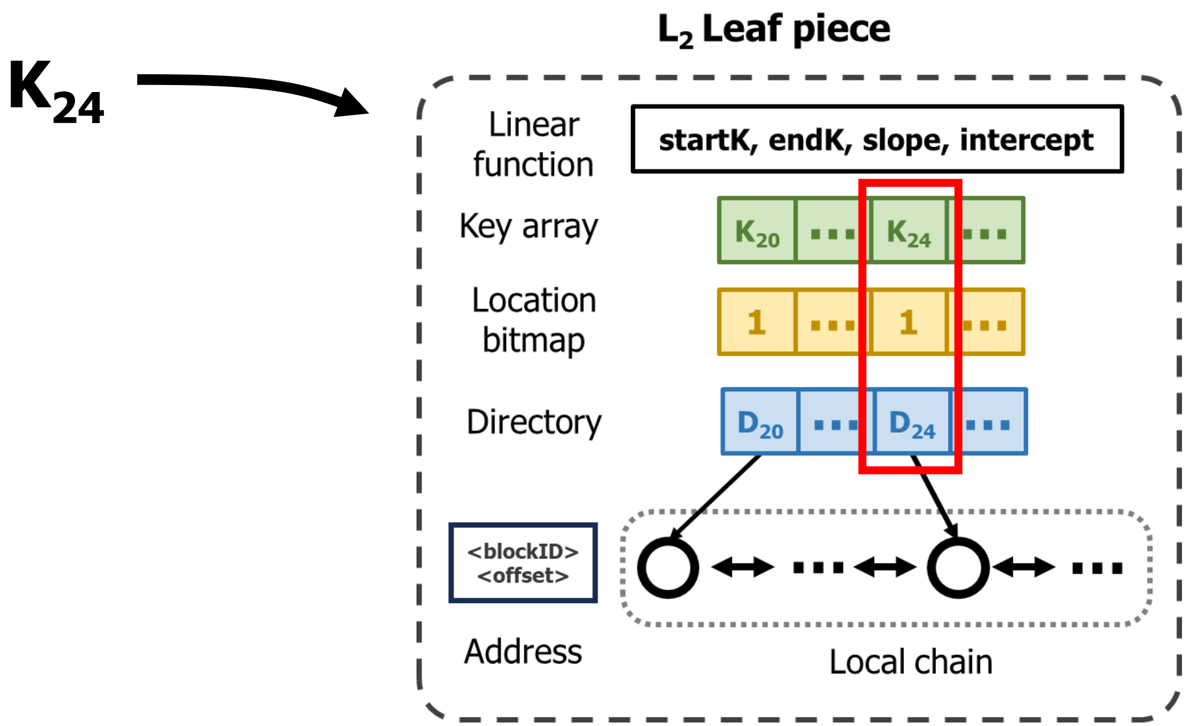


Query Processing

- Point Query

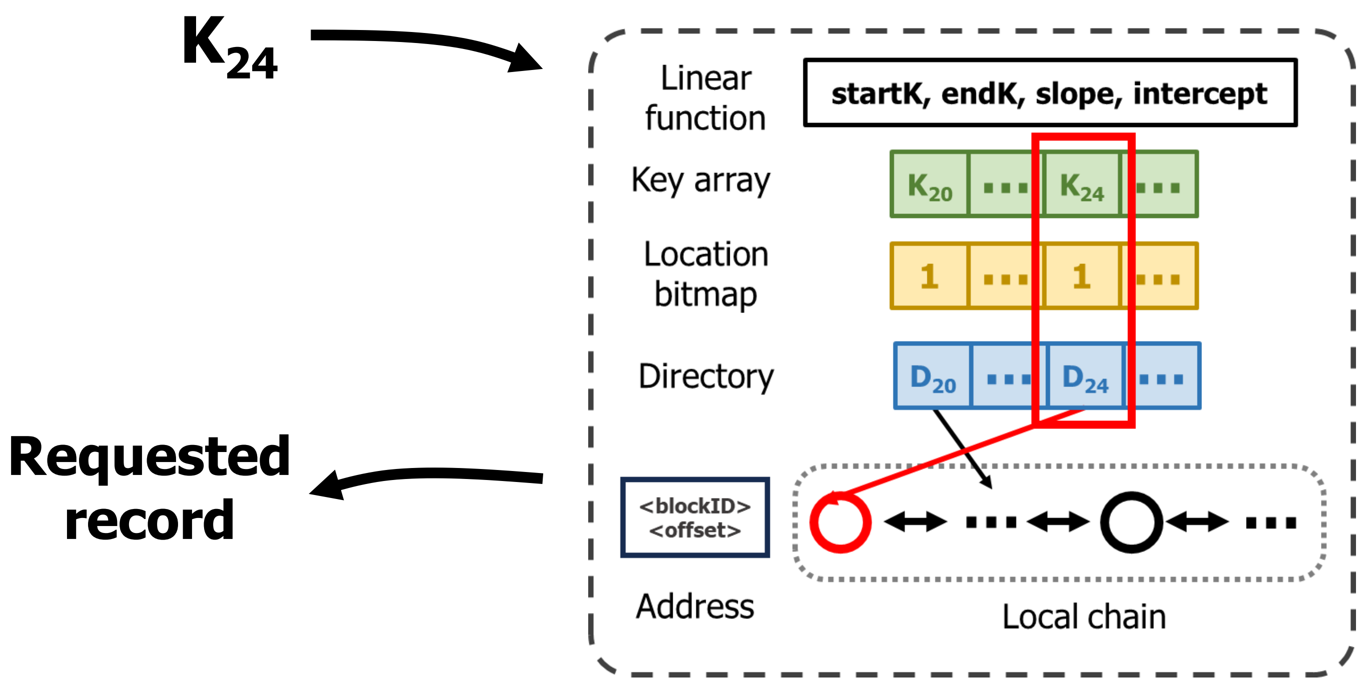
  2. Locate **K** in the piece

     FILM uses the location bitmap to know if k's payload is in memory or on disk



Query Processing

- Point Query
  3. Retrieve the data record and update the adaptive LRU
     Record can be directly accessed using local chain or address

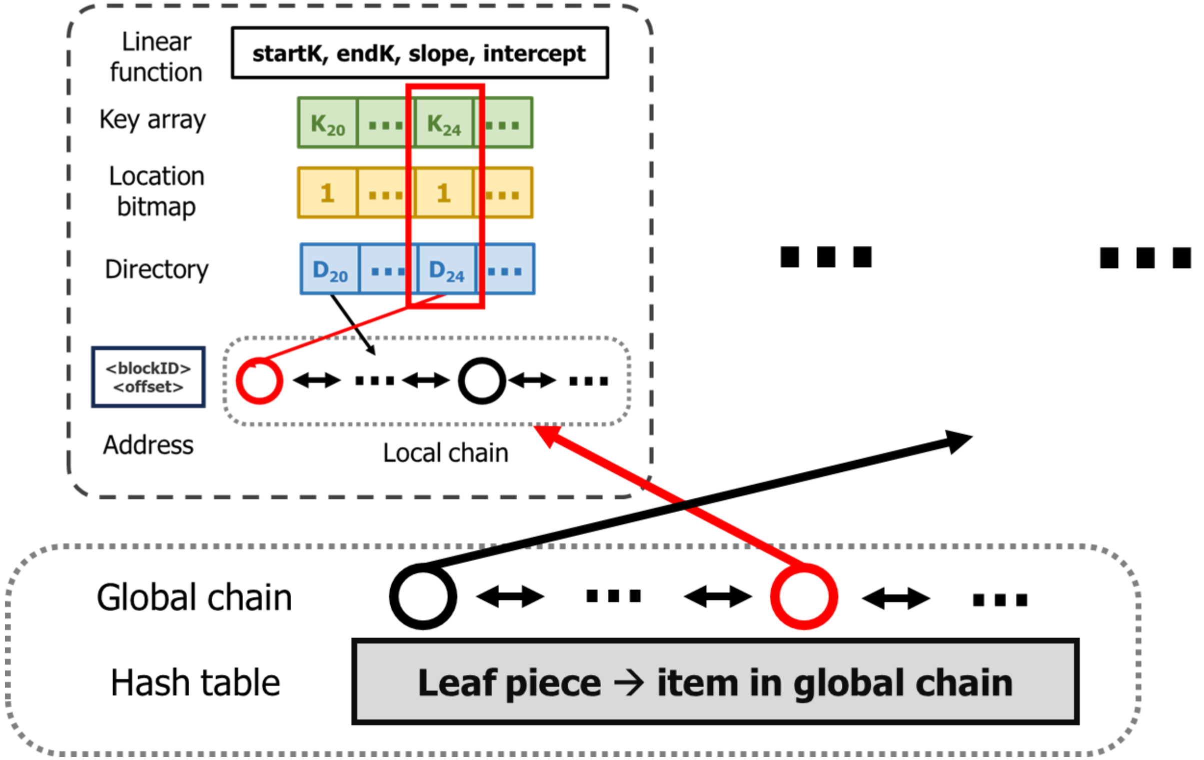


Query Processing

- Point Query

  3. Retrieve the data record and update the adaptive LRU

     The accessed leaf will be moved to the head of the global chain



Query Processing

- Point Query

  3. Retrieve the data record and update the adaptive LRU

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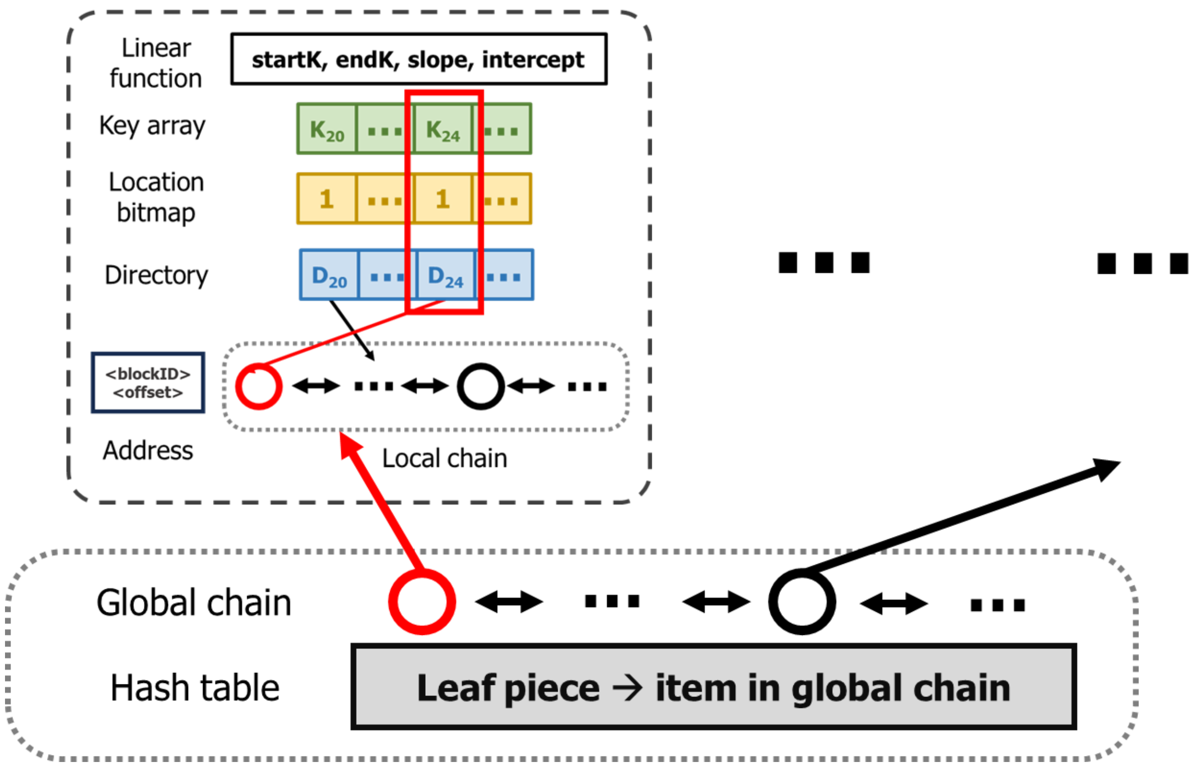
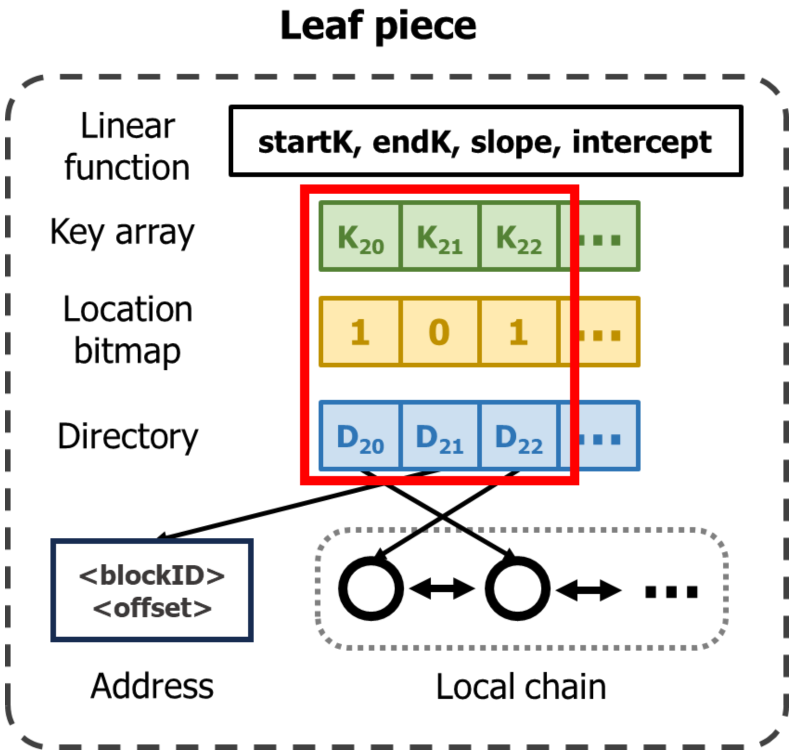


Query Processing

- Range Query
  - FILM handles requested data records similarly whether they reside in a single type or multiple types of storage devices.

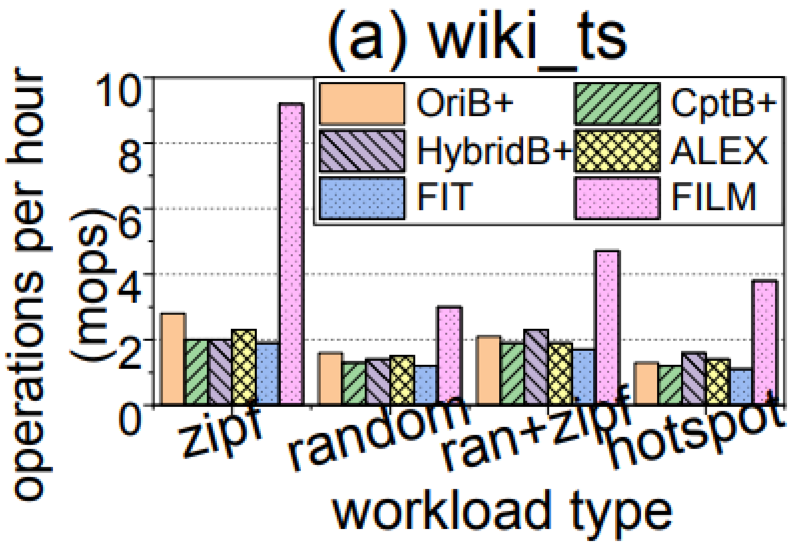


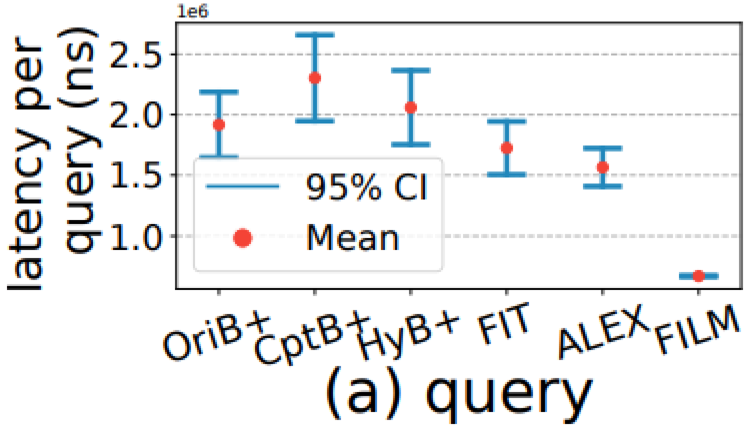
Experiments

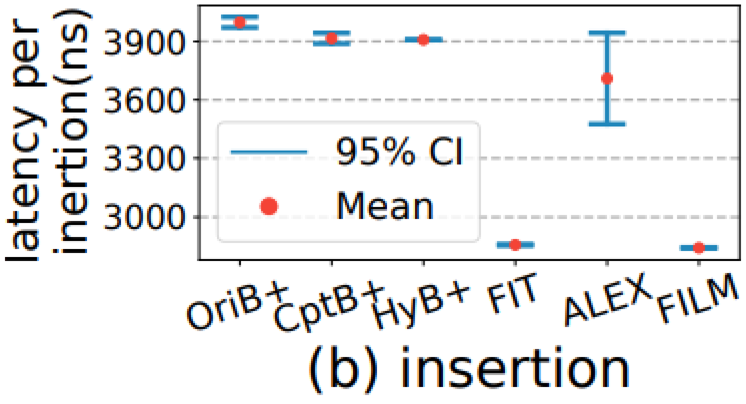
- Baselines and Experiment Setup
  - Comparison(Base Line) : B+tree, HybridB+tree, CptB+tree, Alex, Fitting-Tree
  - Datasets : wiki_ts, books, astro_a, synthetic, YCSB (64bit Key, 128Byte Value)
  - Workload : Zipfian, Hotspot, Random, Zipfian+Random
  - Spec :
    - 3.6GHz Intel CPU with 256KB L1 cache
    - 128GB memory (4 × 32GB)
    - 557GB disk
    - Single thread
    - Direct I/O

Experiments

- Comparison with Baselines
  - Insertion and query performance(Avg. 4GB All dataset, 1:1 , 1 hour)





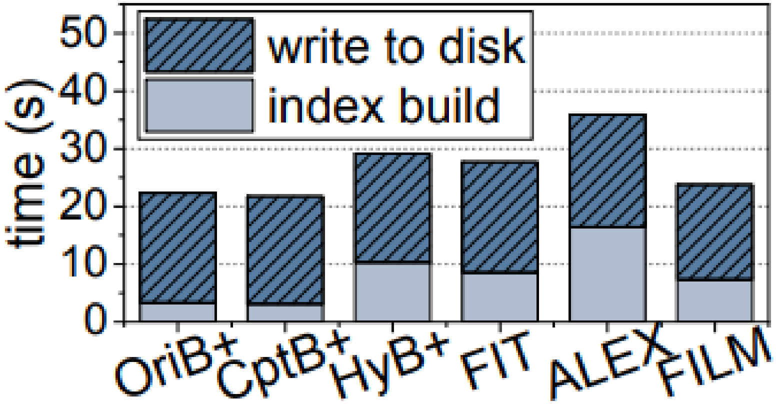


FILM has a 2-5 times advantage over base line in terms of insertion and query performance.

Film also has the lowest latency and more stable performance.

Experiments

- Comparison with Baselines
  - Index construction



(c) books

The learned index has advantages over traditional indexes in memory usage, but correspondingly, it has disadvantages in build time (about 2.2~2.5 times).

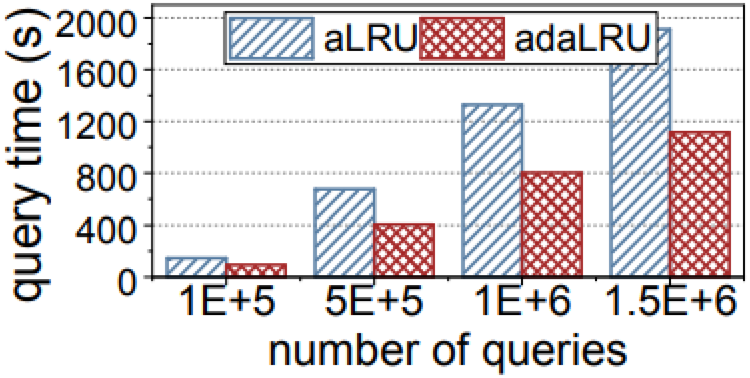
Also, due to occupying less memory, it has more advantages in writing to disk.

Experiments

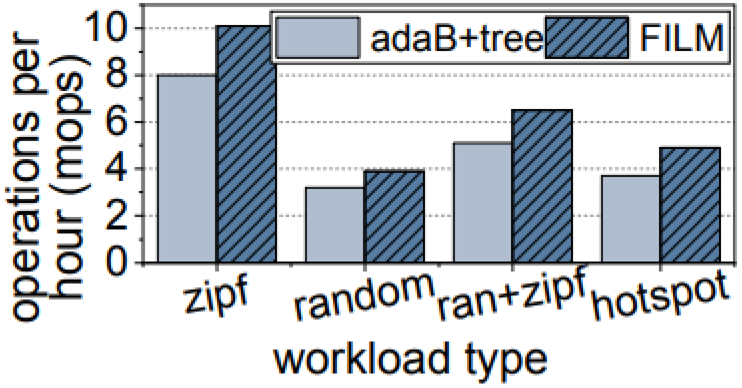
- Comparison with Baselines

  - LRU overhead(books, 4GB dataset, 100000 random queries)

    aLRU : LRU with a sampling rate of 0.01
    adaLRU : Adaptive LRU



(a) aLRU vs. adaptive LRU

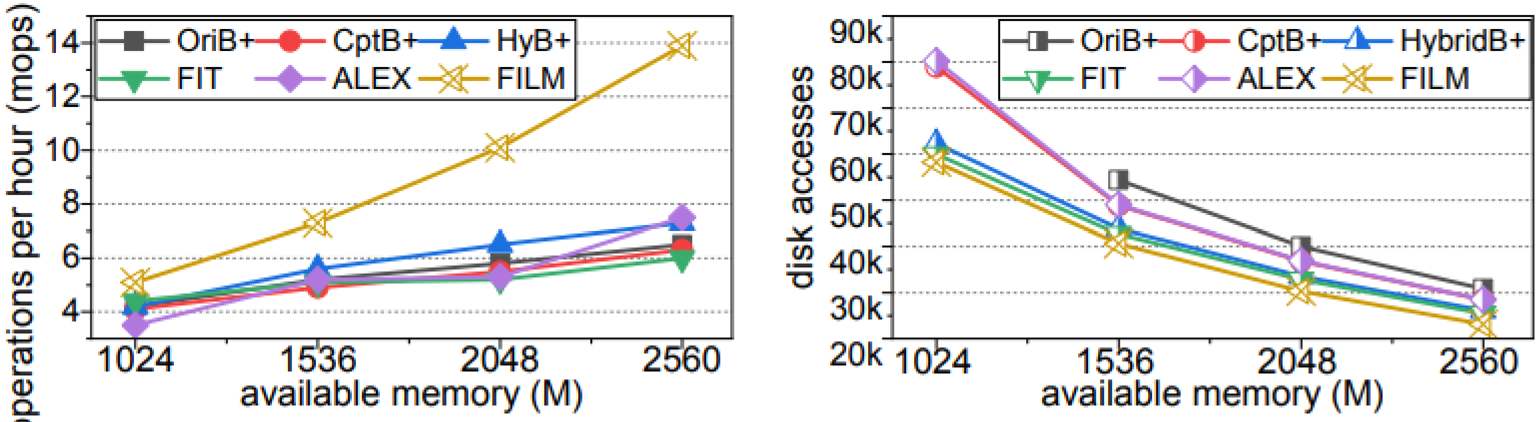


(b) adaB+tree vs. FILM

On LRU, adaLRU is superior to aLRU.
On the index, FILM is superior to traditional indexes.

Experiments

- Study of Environment Parameters
  - Available memory(4GB wiki_ts dataset, Zipfian workload)

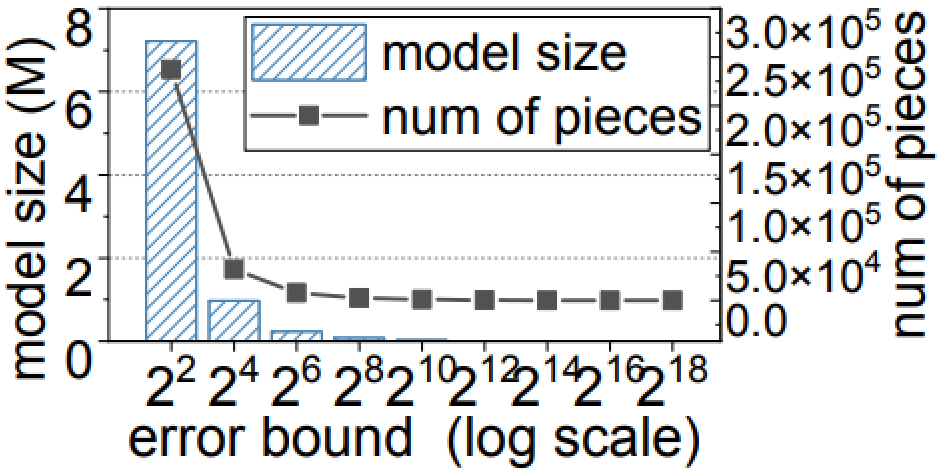


(a) total number of operations (b) number of disk accesses

Increasing memory can increase the number of operations per unit time and reduce disk io, with FILM gaining more significant benefits in this regard.

Experiments

- Sensitivity to Data and Model Parameters
  - Error bound ε

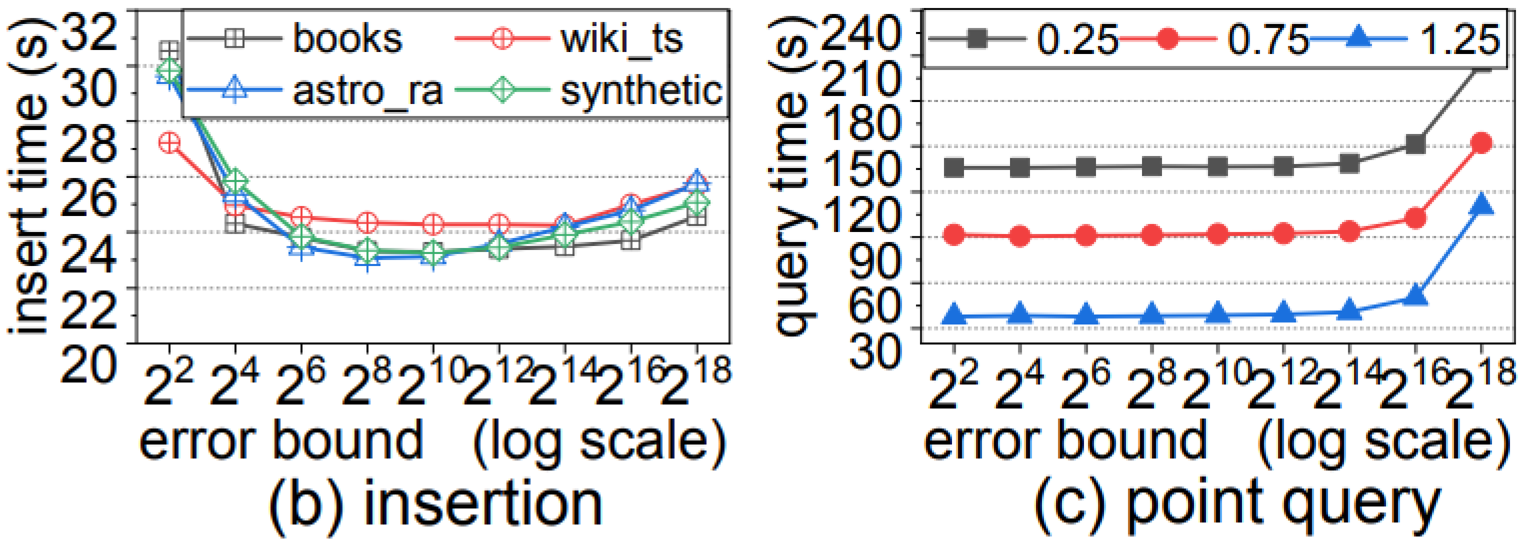


(a) model size

When the error bound increases from 4 to 16, the sharp decrease in the number of pieces fitted by FILM leads to a decrease in the memory occupied by FILM, which then stabilizes.

Experiments

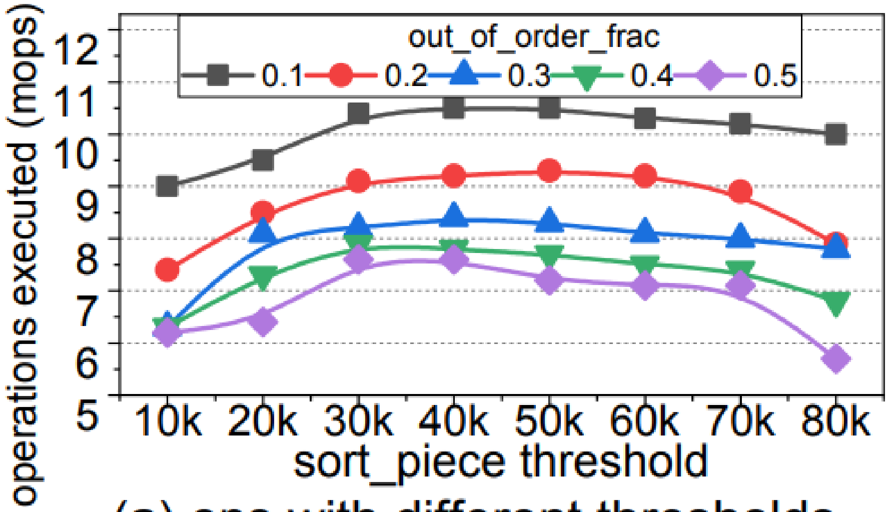
- Sensitivity to Data and Model Parameters
  - Error bound ε



FILM within the range of 16 to 2^{12} ε having the best performance.

Experiments

- Sensitivity to Data and Model Parameters
  - Handling Out-of-Order Insertions(sort_piece)



(a) ops with different thresholds

Both too small and too large sort pieces can lead to performance loss.
30000~70000 is the optimal range.

Thank you