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

Ma, Chaohong, et al. VLDB 2022

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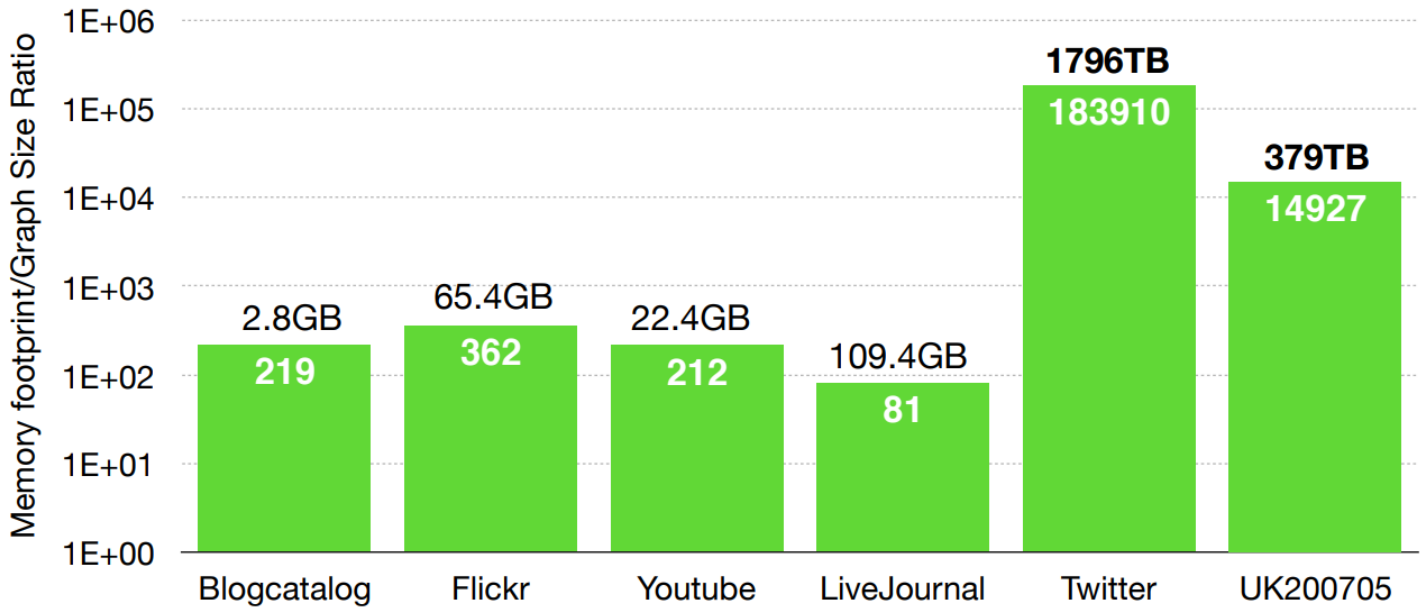
Contents

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)

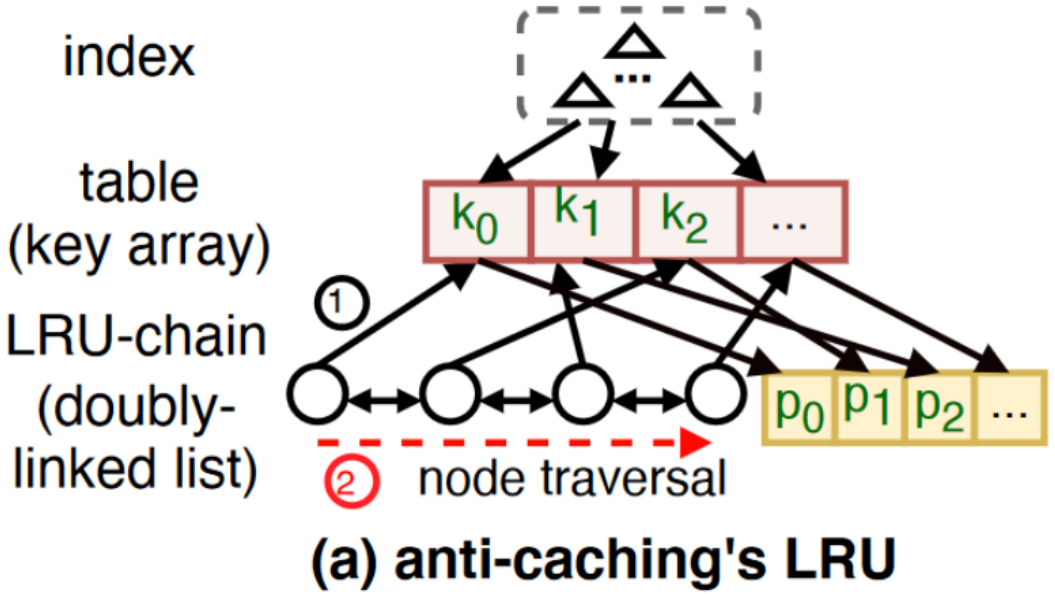
Introduction

- 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

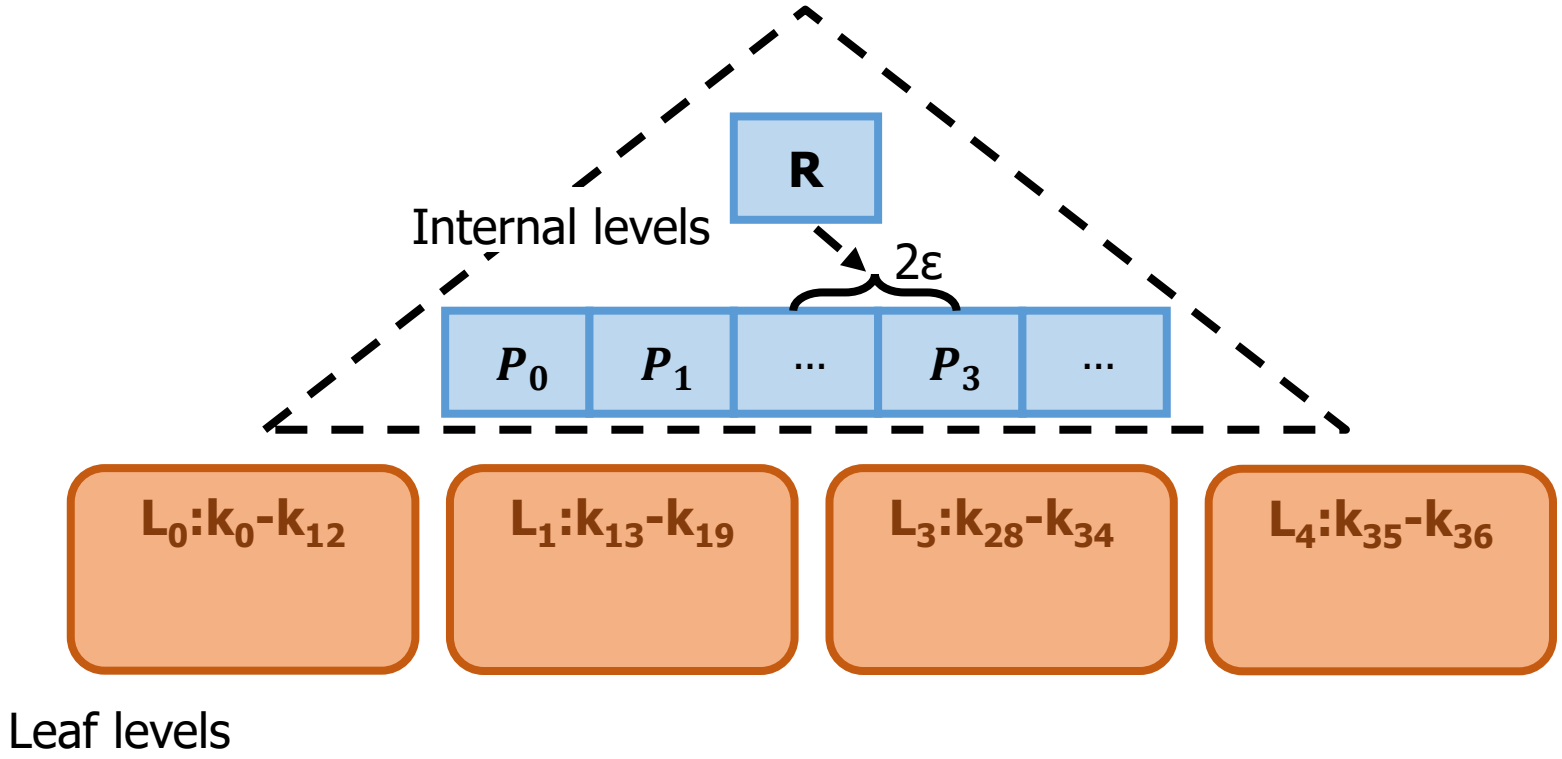
- Adaptive LRU for efficient cold data identification, cost-effective management

3. Unified Tree Structure

- Stable tree structure minimizes maintenance despite data swapping

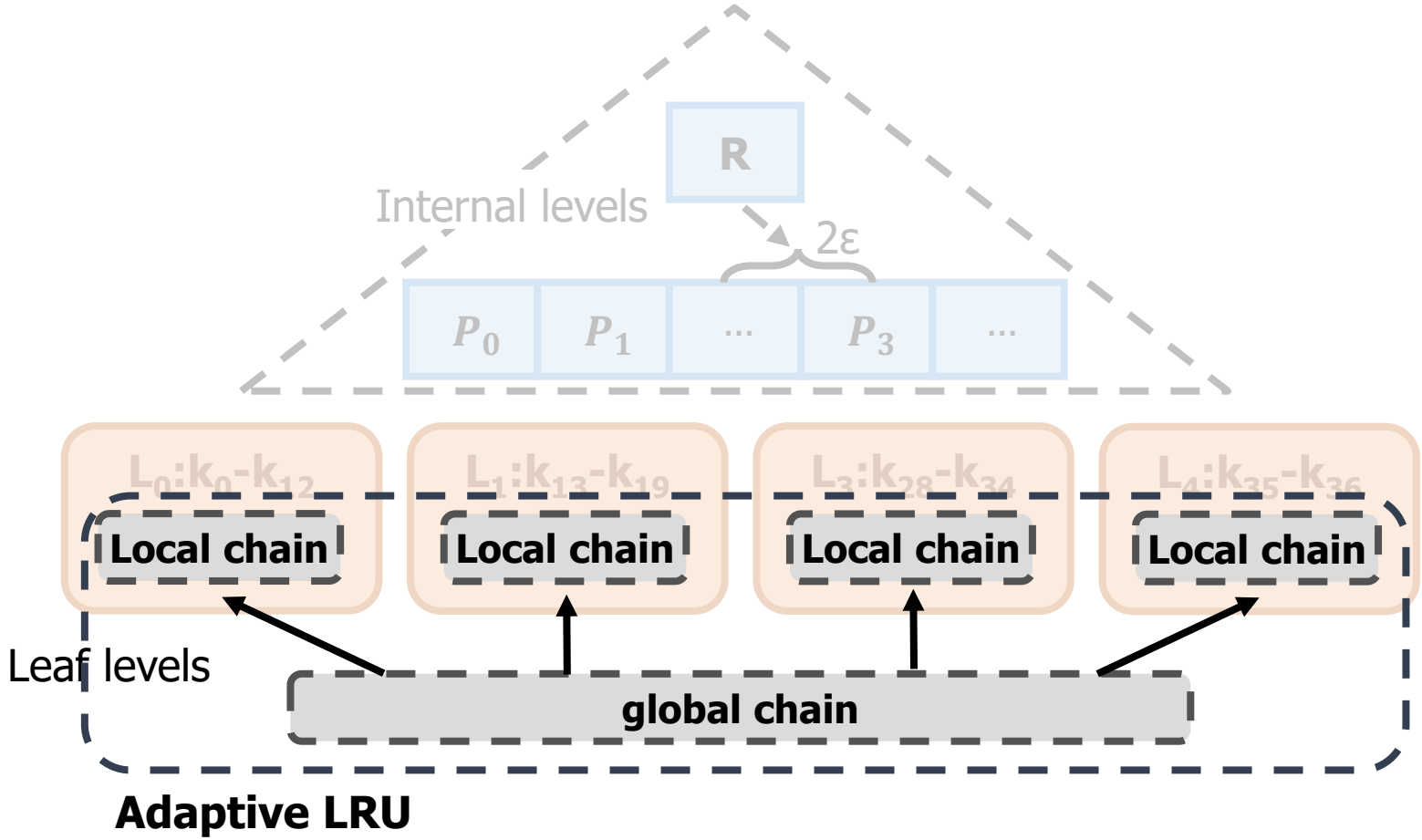
Design

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



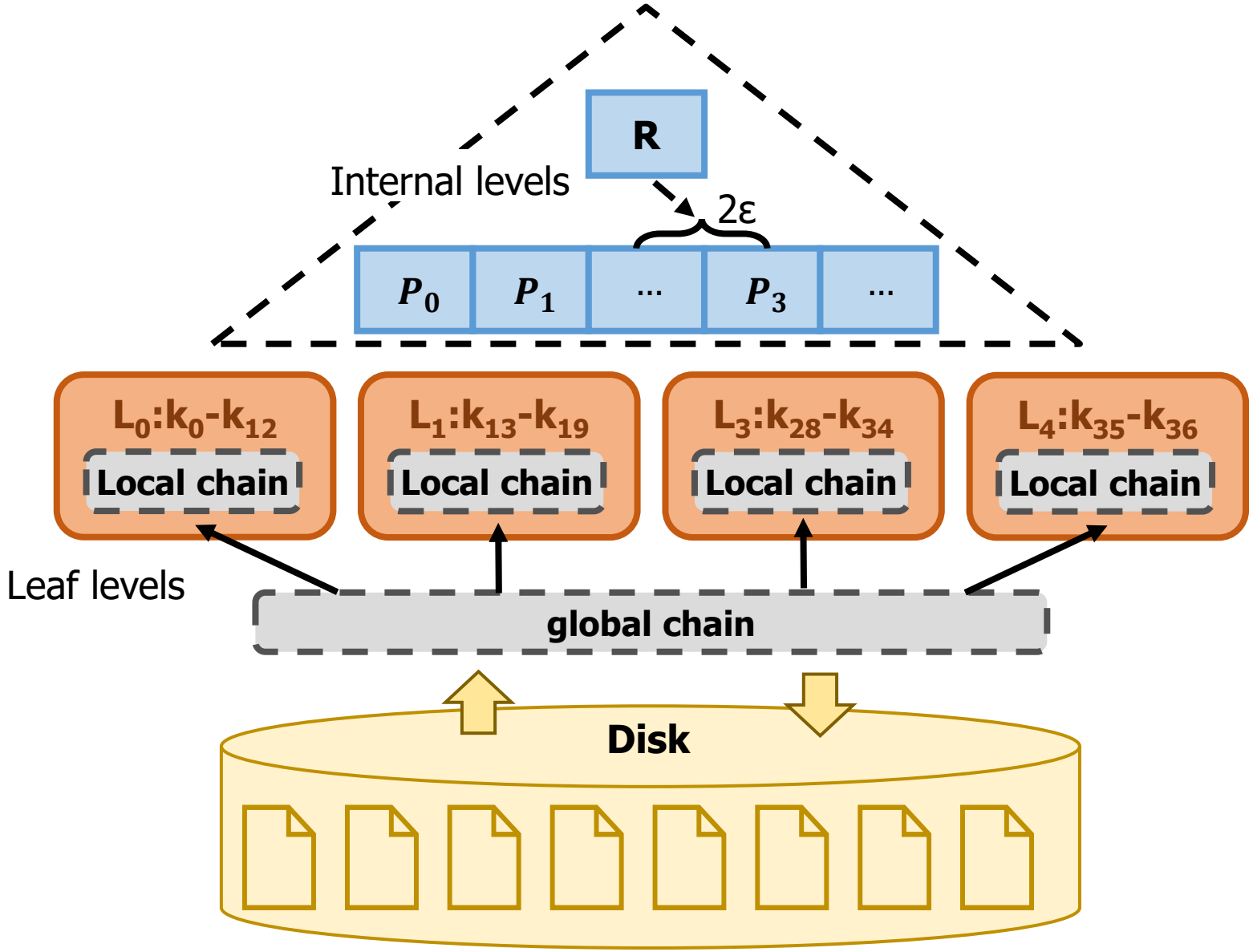
Design

- 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)

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

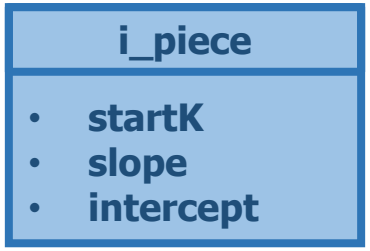
  - Newly inserted key breaking constraint is inserted into new piece,
    this key is called 'break_k'

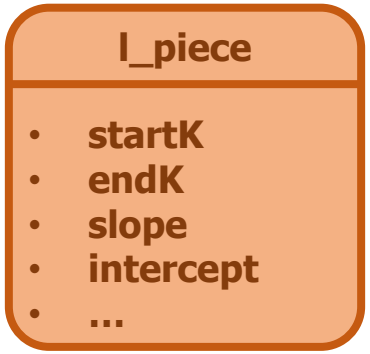
The Design of Piece

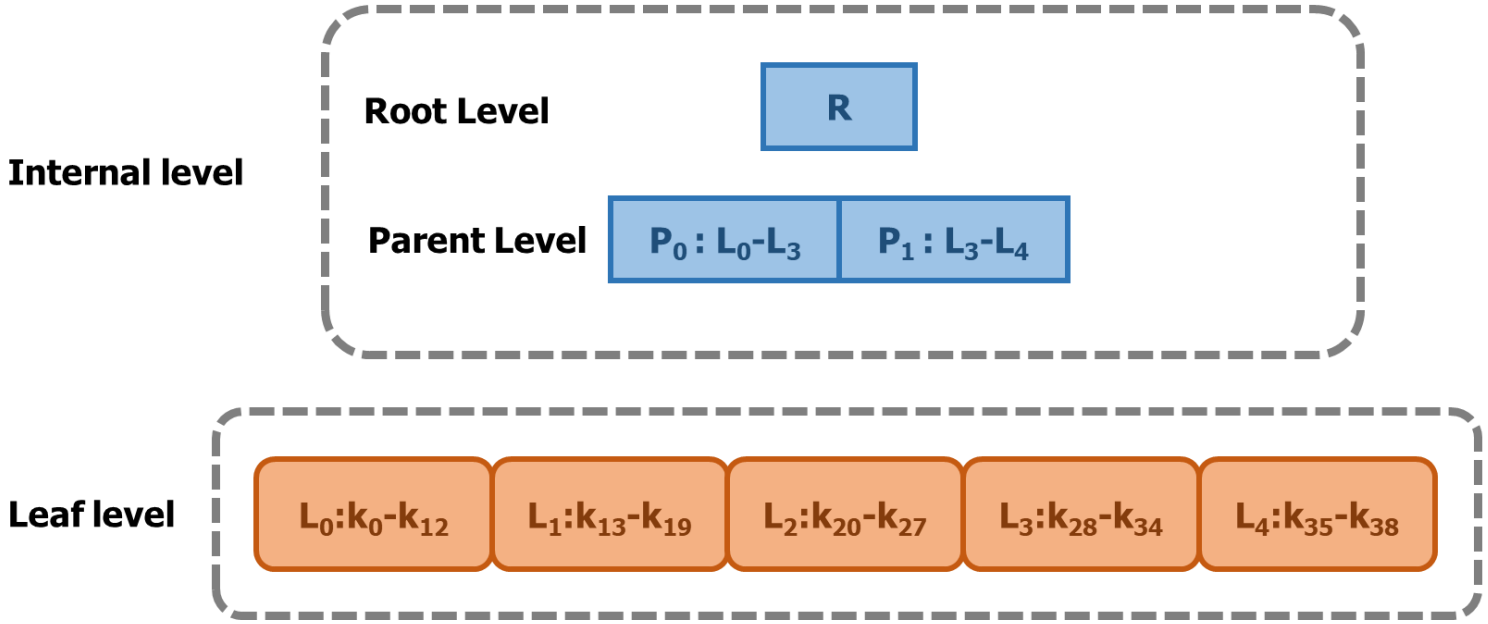
i_piece

l_piece

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





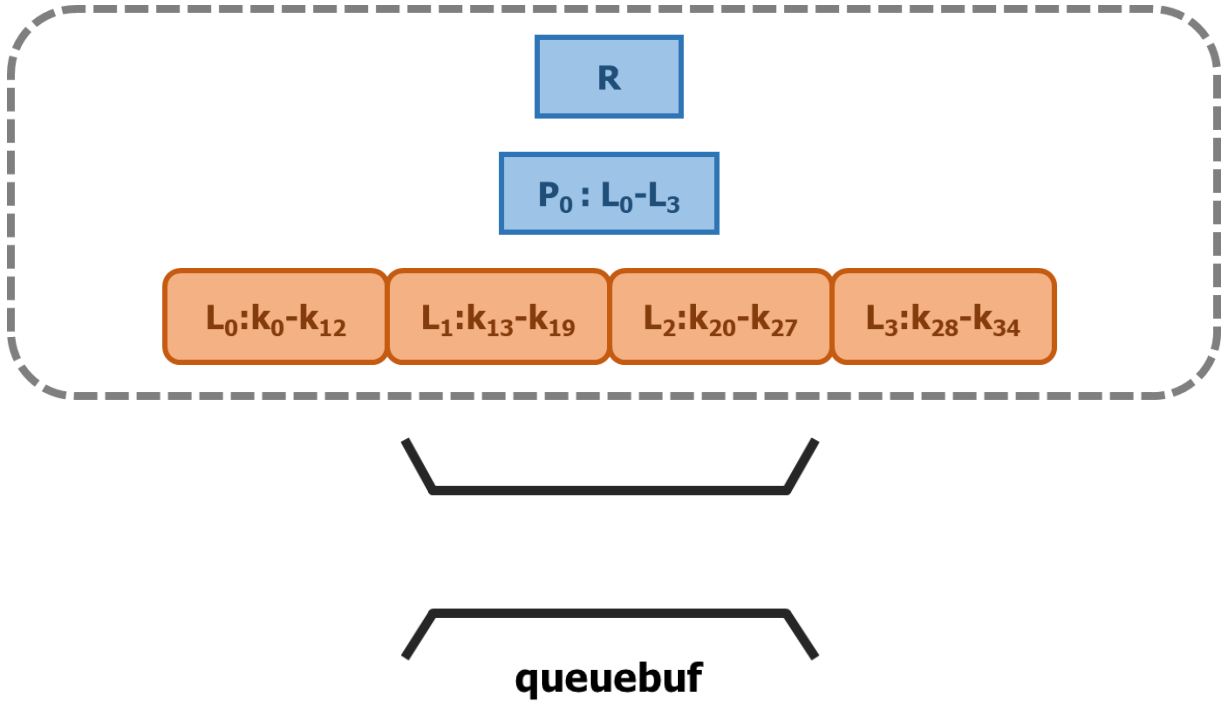


Dynamic Learned Model

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

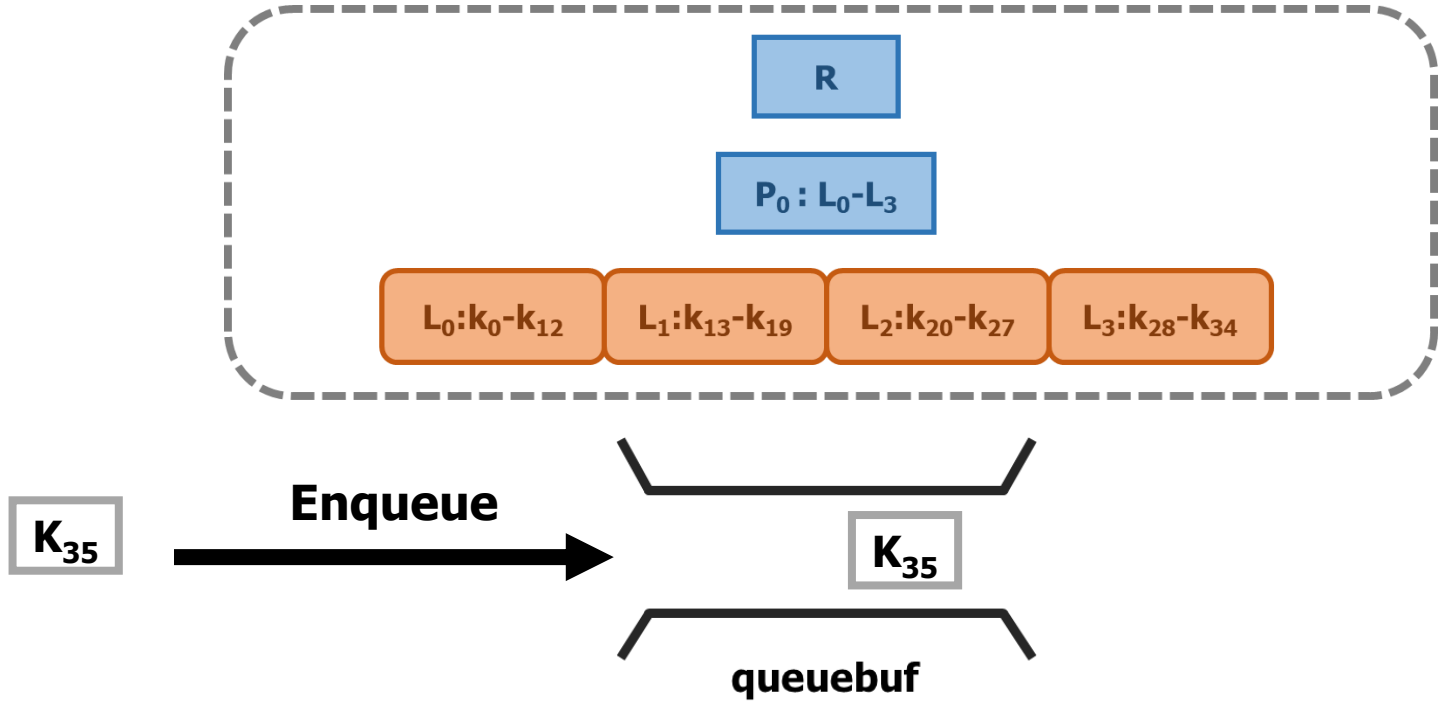


Dynamic Learned Model

i_piece

l_piece

- 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

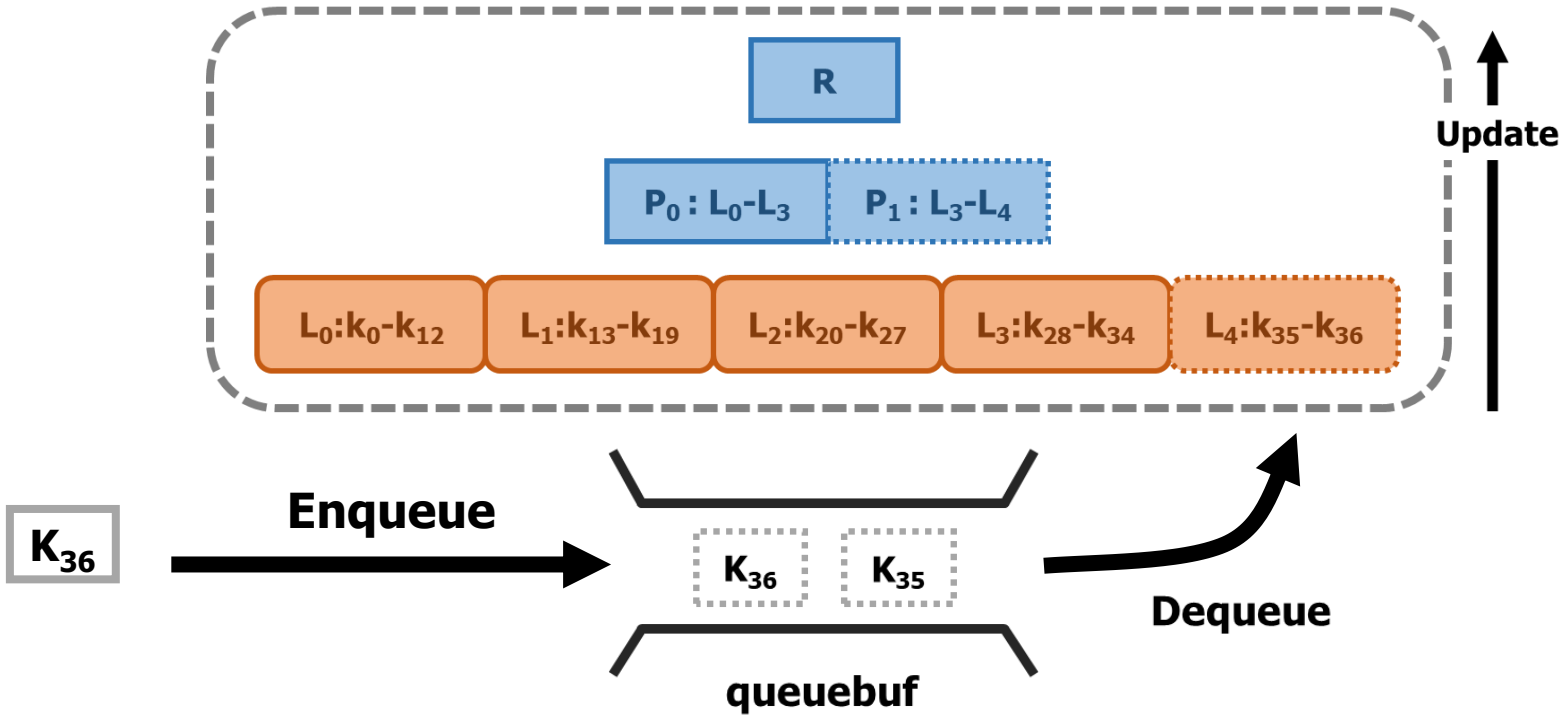


Dynamic Learned Model

i_piece

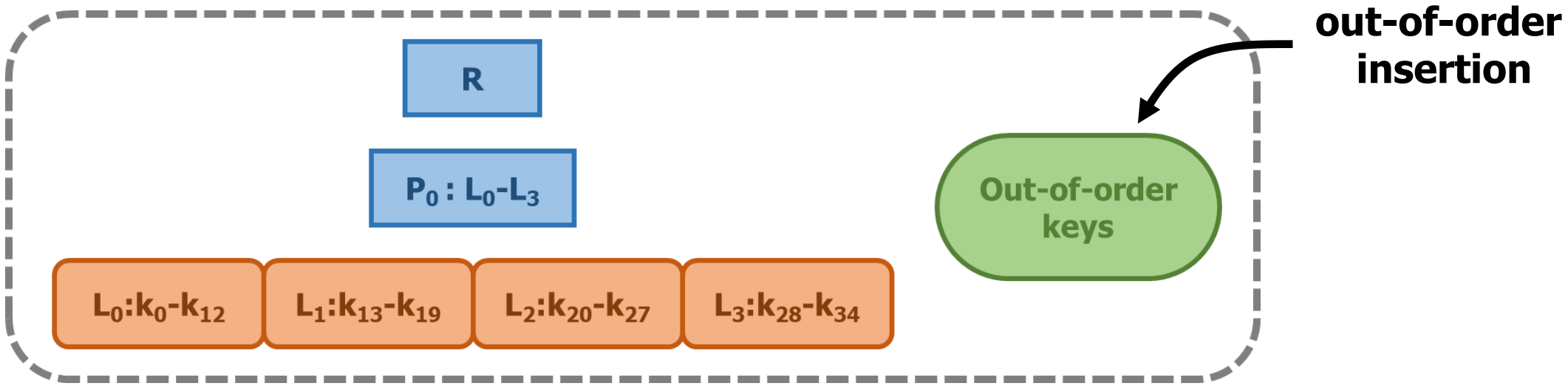
l_piece

- 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



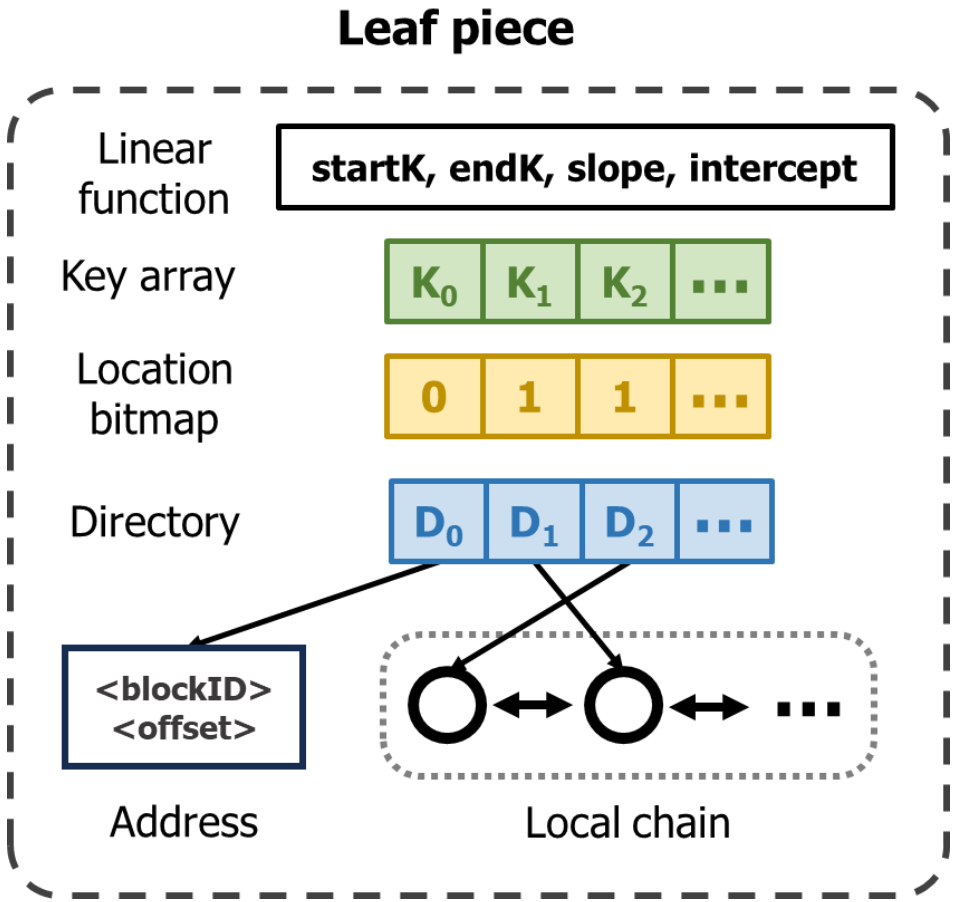
Dynamic Learned Model

- 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



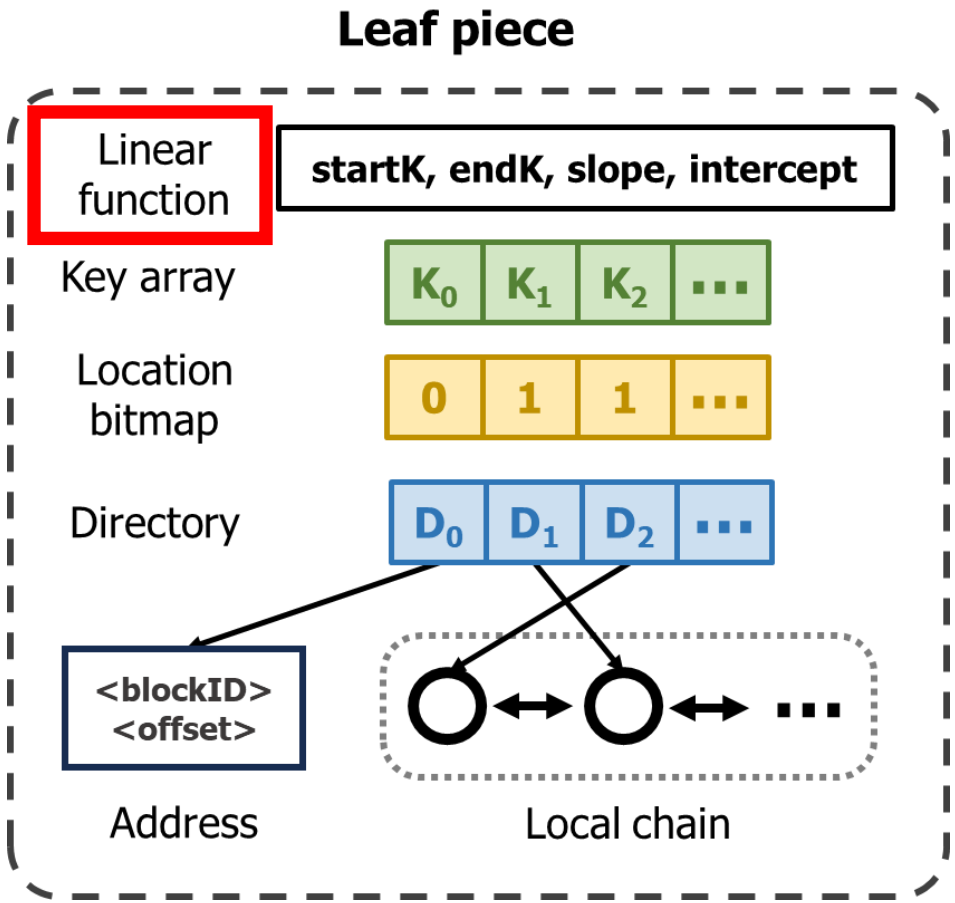
Dynamic Learned Model

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



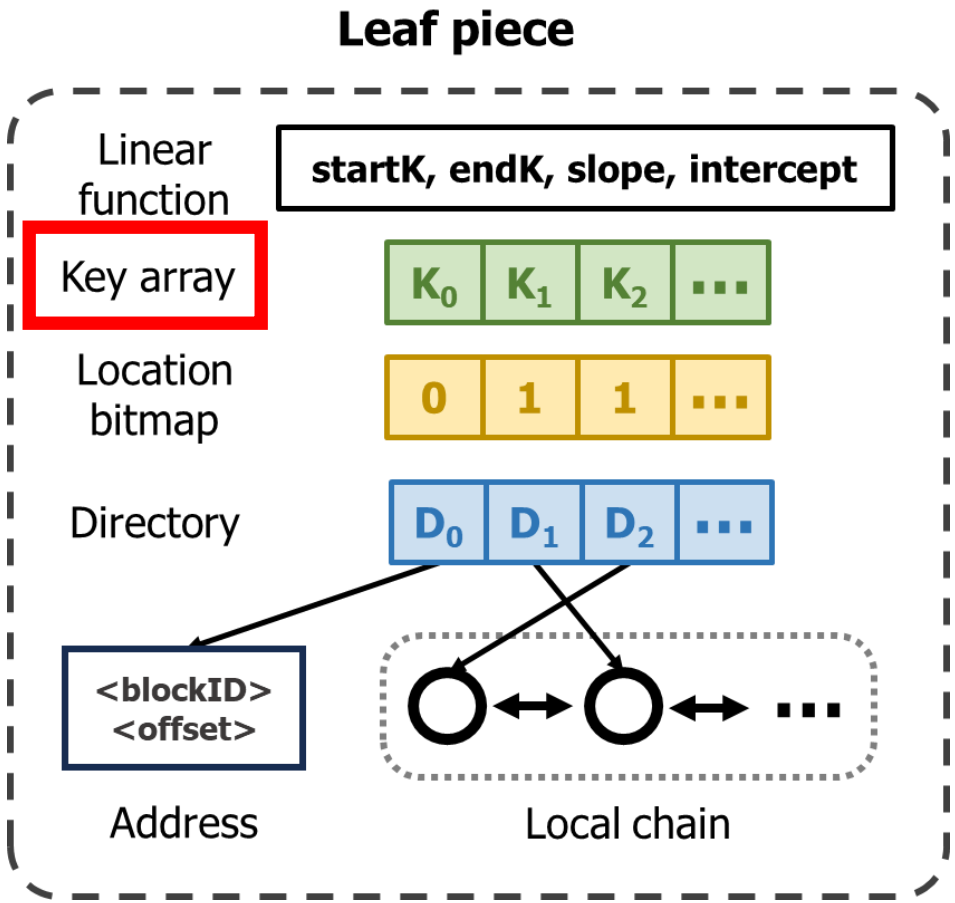
Dynamic Learned Model

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



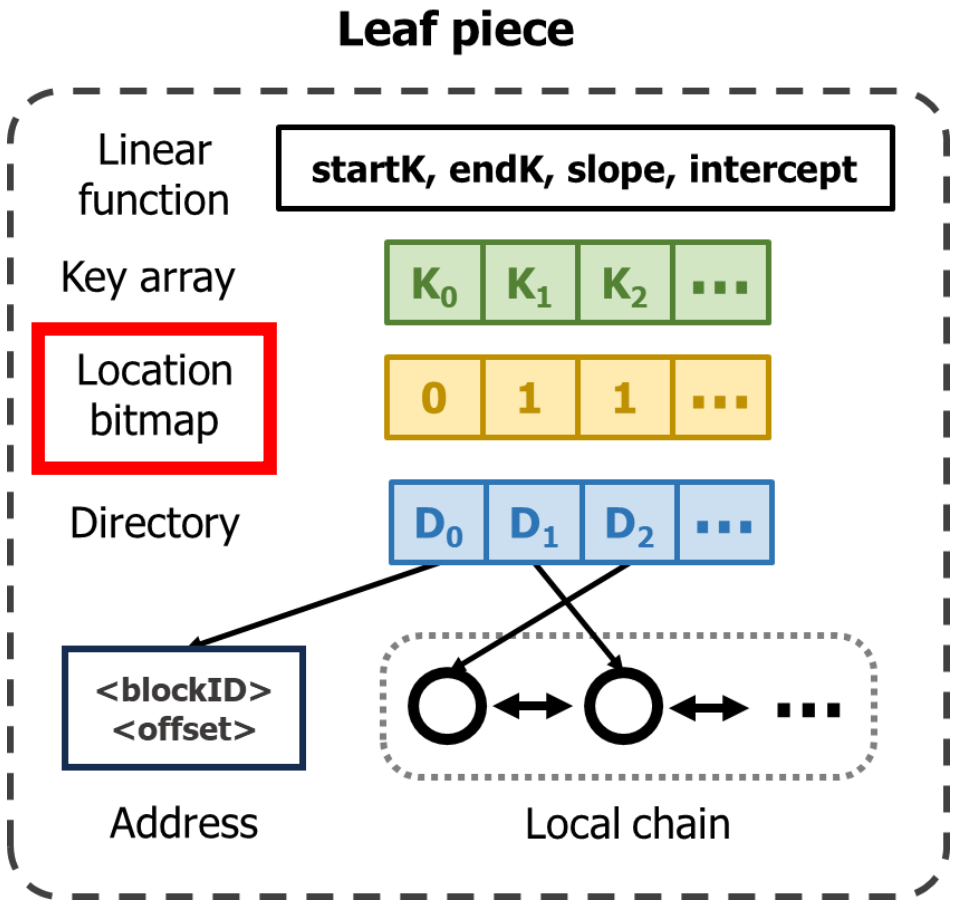
Dynamic Learned Model

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



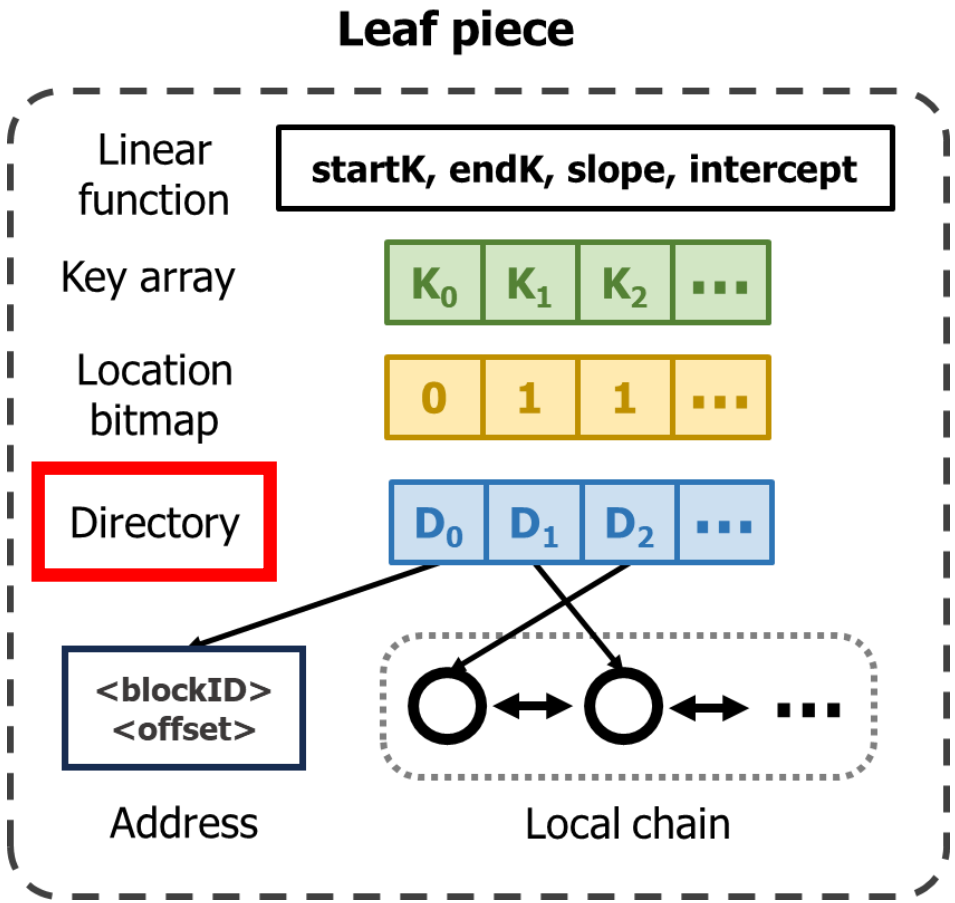
Dynamic Learned Model

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



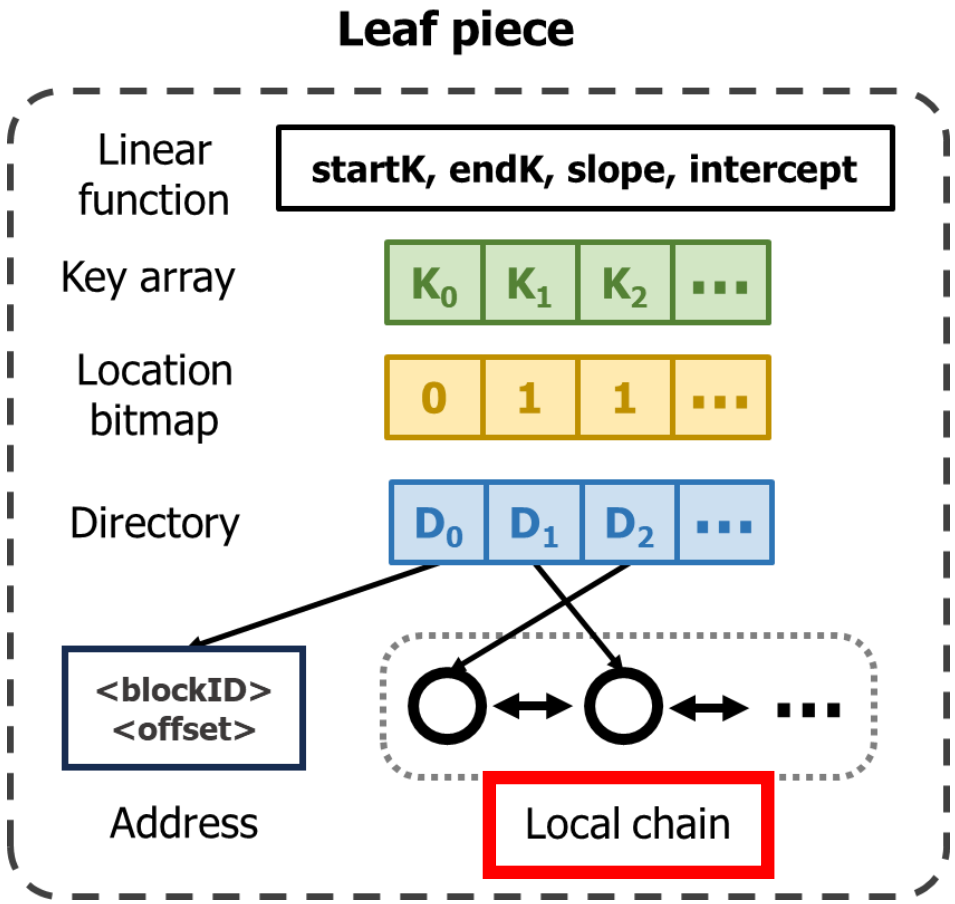
Dynamic Learned Model

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



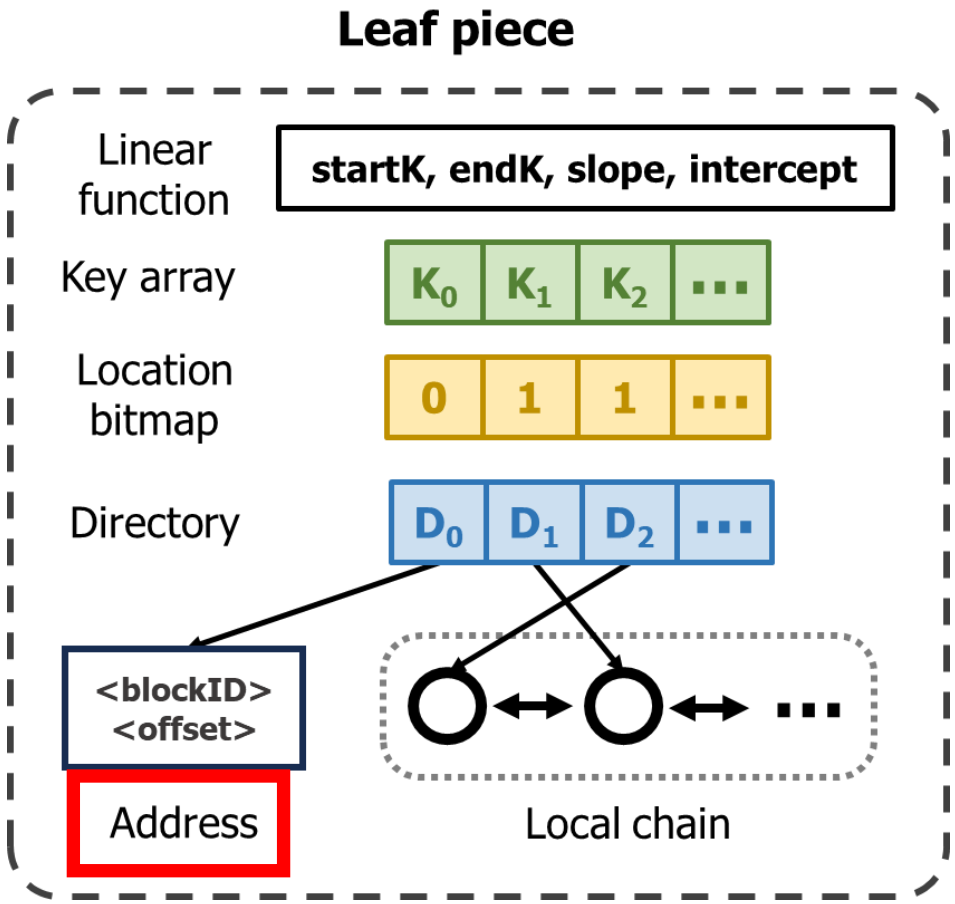
Dynamic Learned Model

- Leaf piece of FILM
  - Linear function
  - Key array
  - Location bitmap
  - Directory
  - Local chain
    - Stores the payloads of the keys
    - More details in next section
  - Address



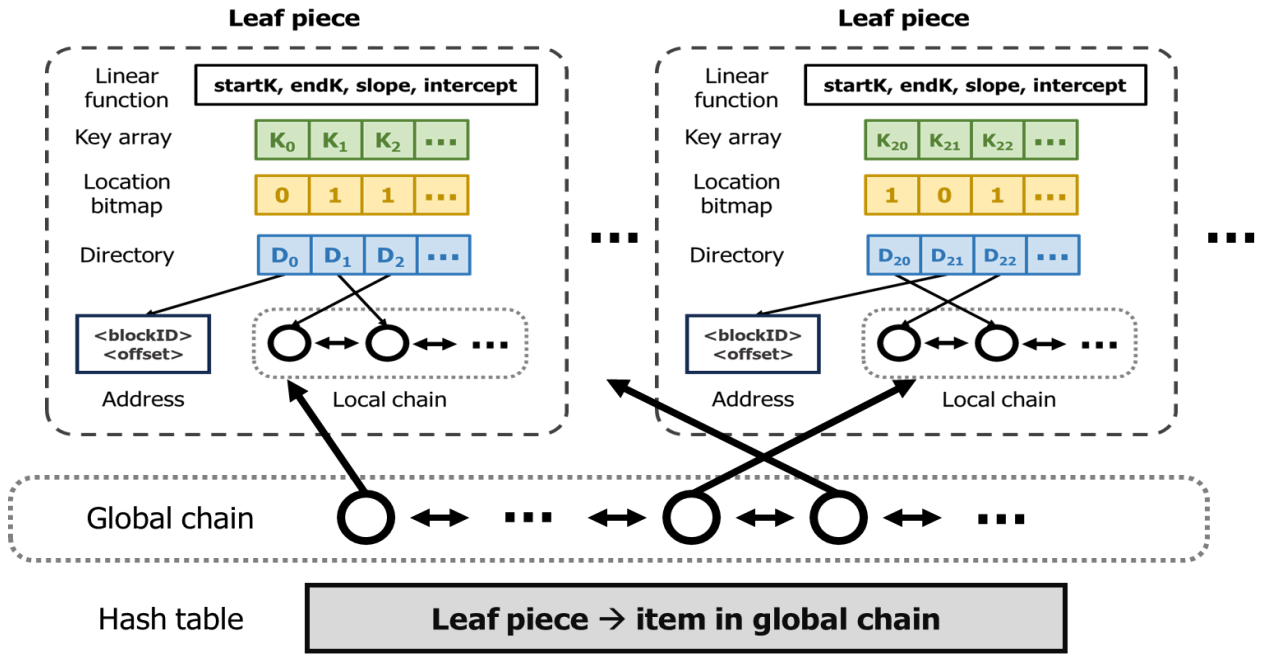
Dynamic Learned Model

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



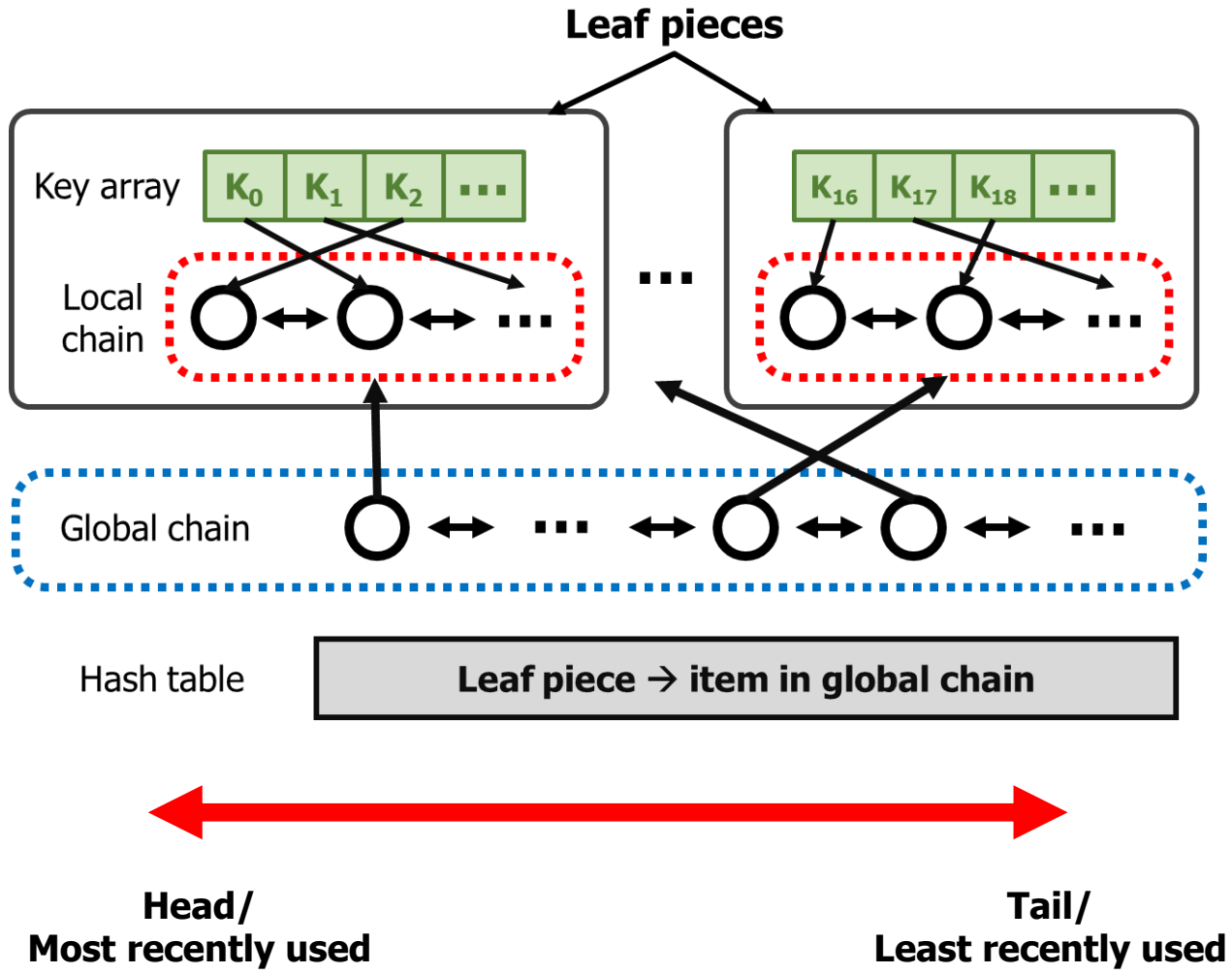
Dynamic Learned Model

- 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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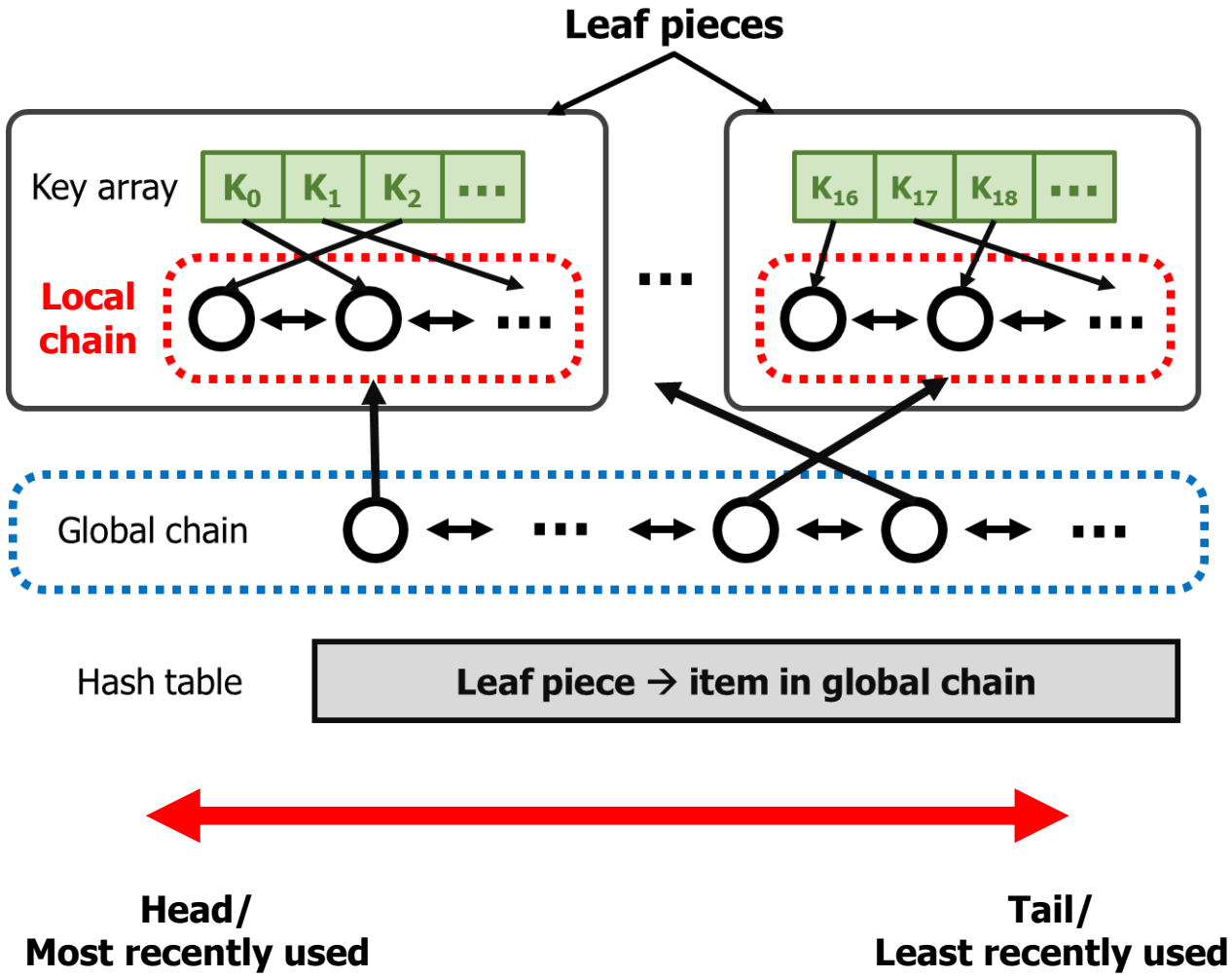
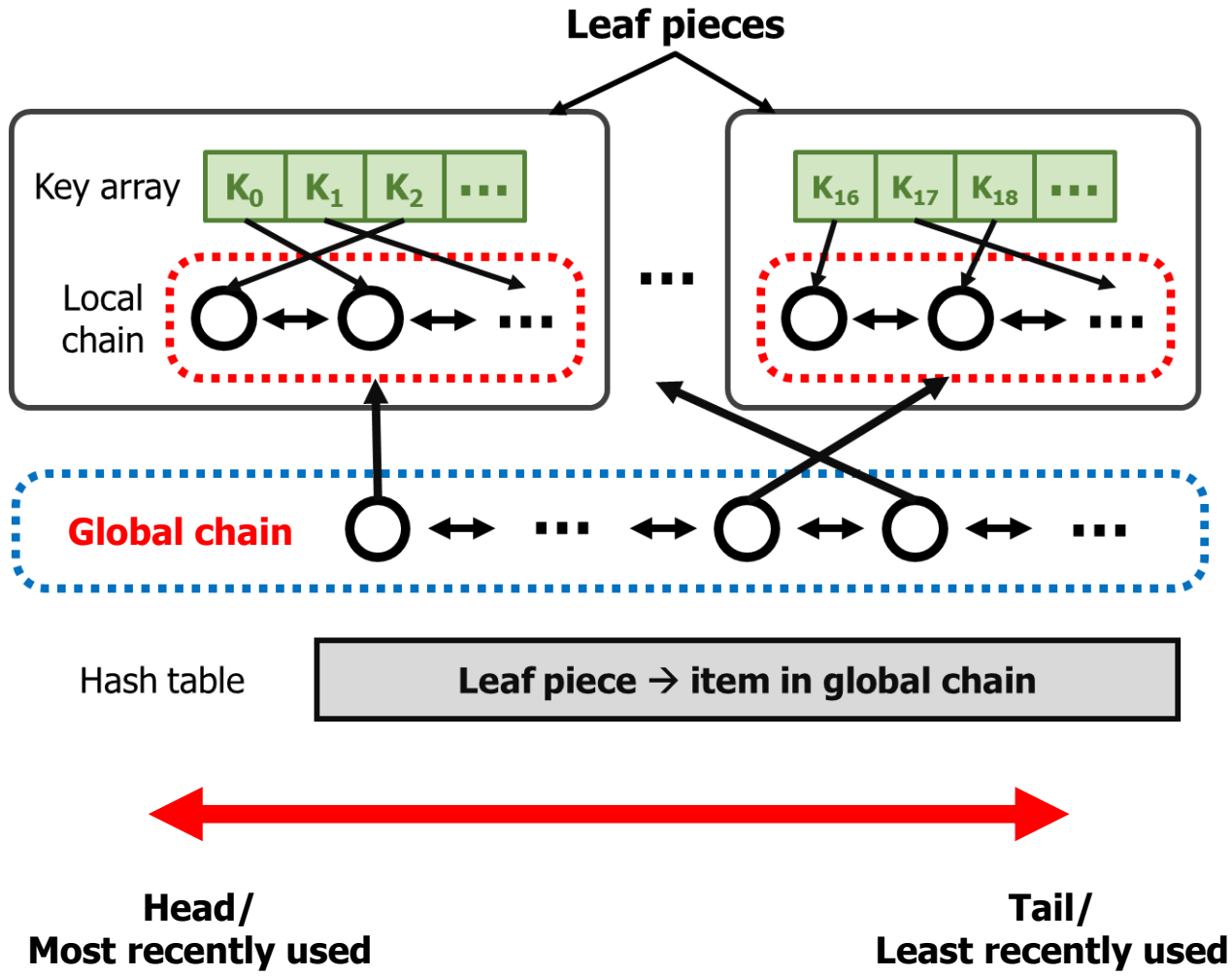


Adaptive LRU

- Local chain
  - A component in a leaf piece
  - Maintain LRU order of the keys
  - Stores the payloads of the keys

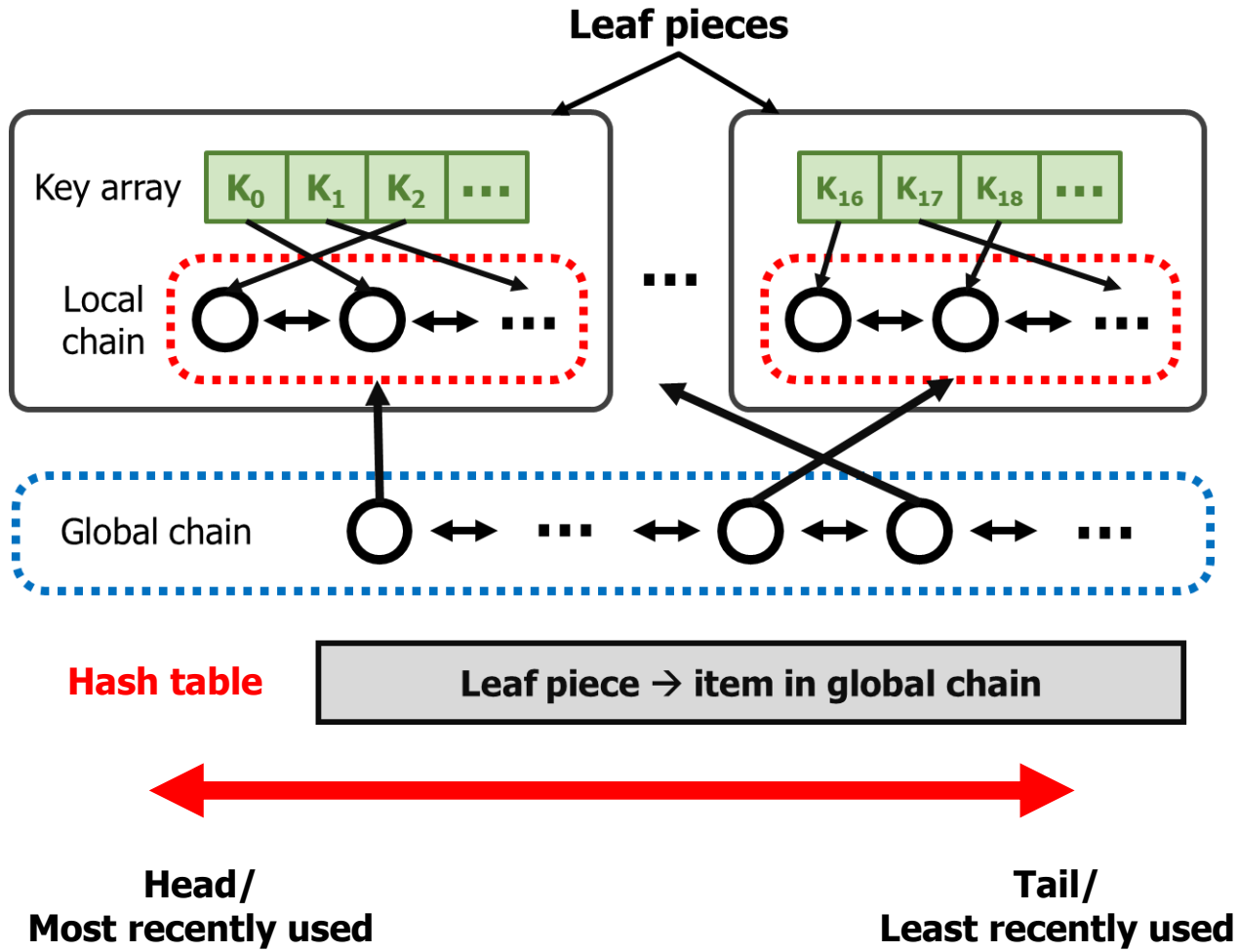
- **Global chain**
  - Points to a leaf piece
  - Maintain LRU order of the l_pieces
  - Track the global data access order across pieces

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



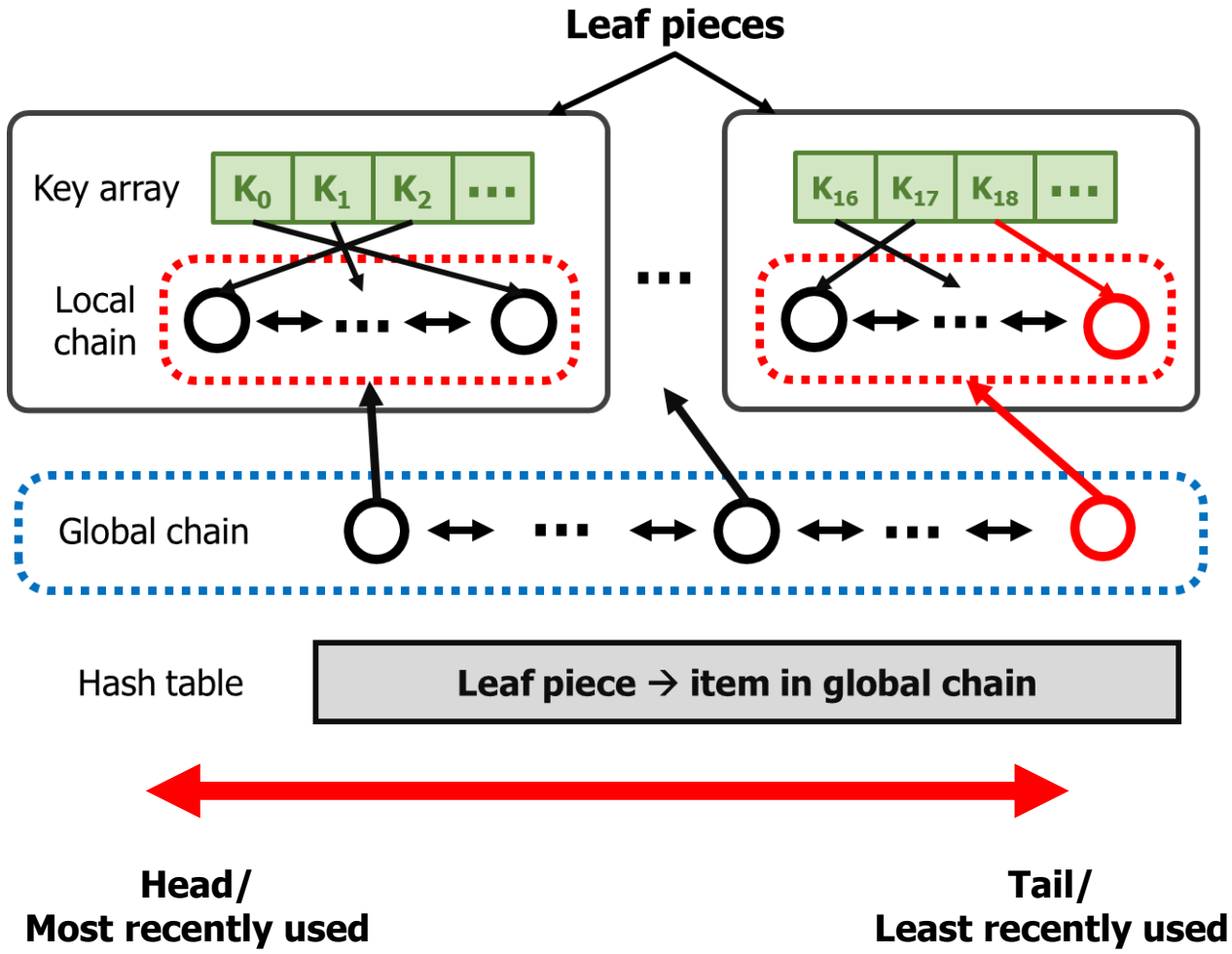
Adaptive LRU

- 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



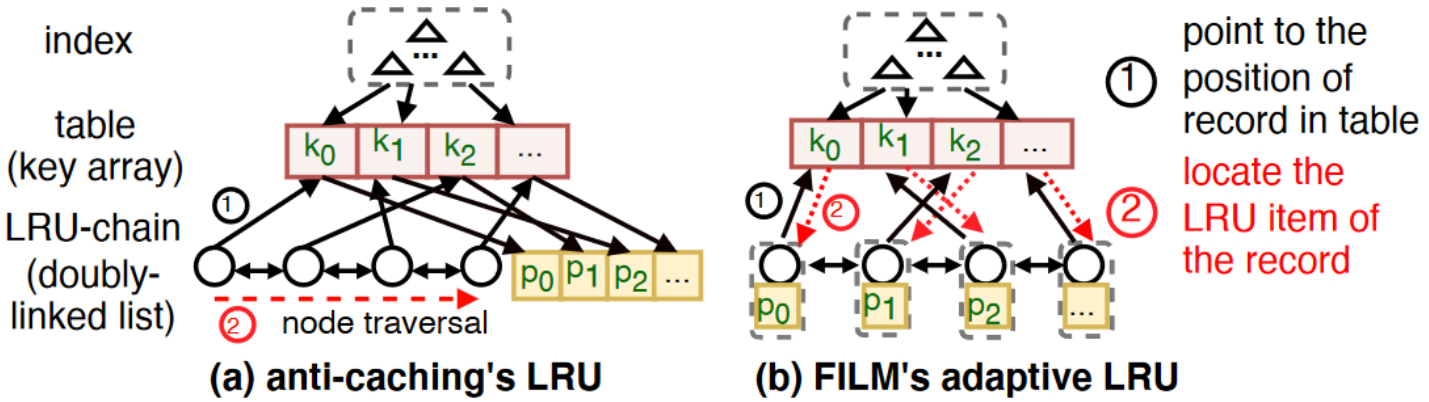
Adaptive LRU

- 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



Note: In anti-caching, the pointers of LRU chain are embeds in the records' headers. To show the difference when locating LRU items more intuitive, we separate them in this toy example.

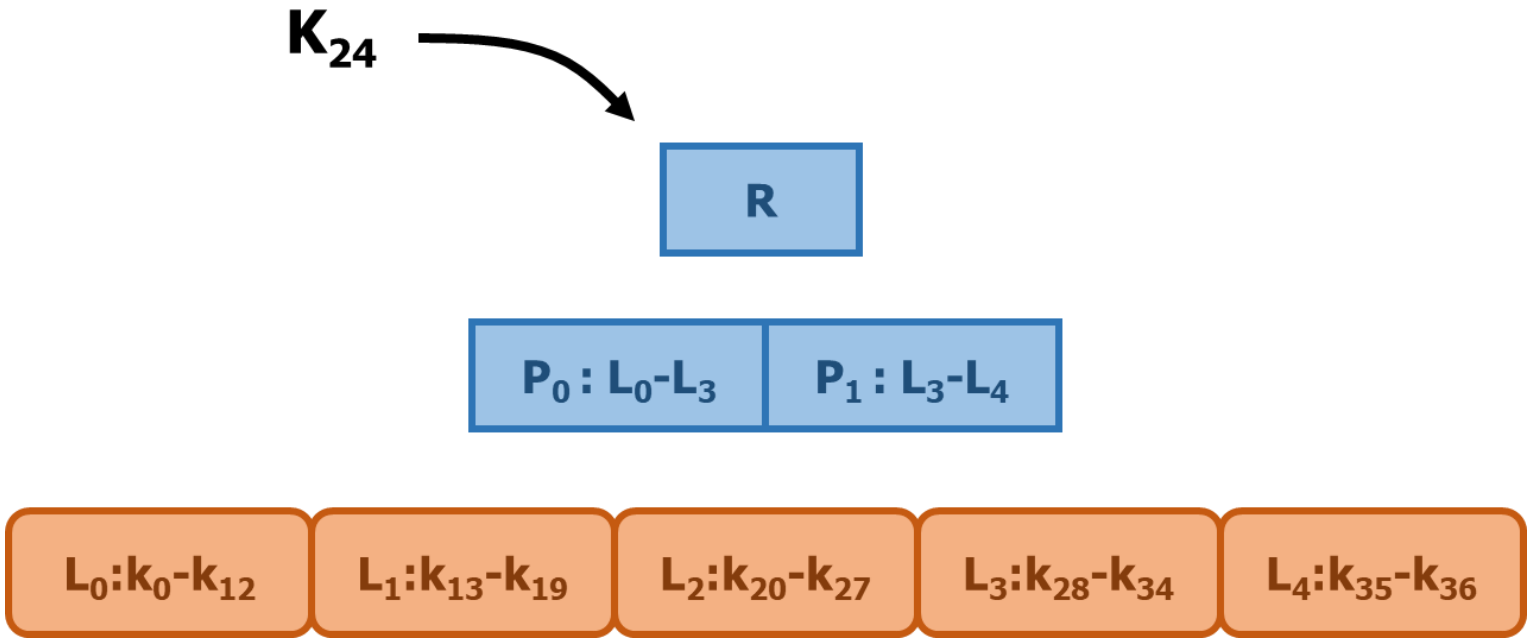
Fig. 4: LRU in anti-caching vs. adaptive LRU in FILM

Query Processing

- Point Query

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

     Recursively predict the candidate pieces



Query Processing

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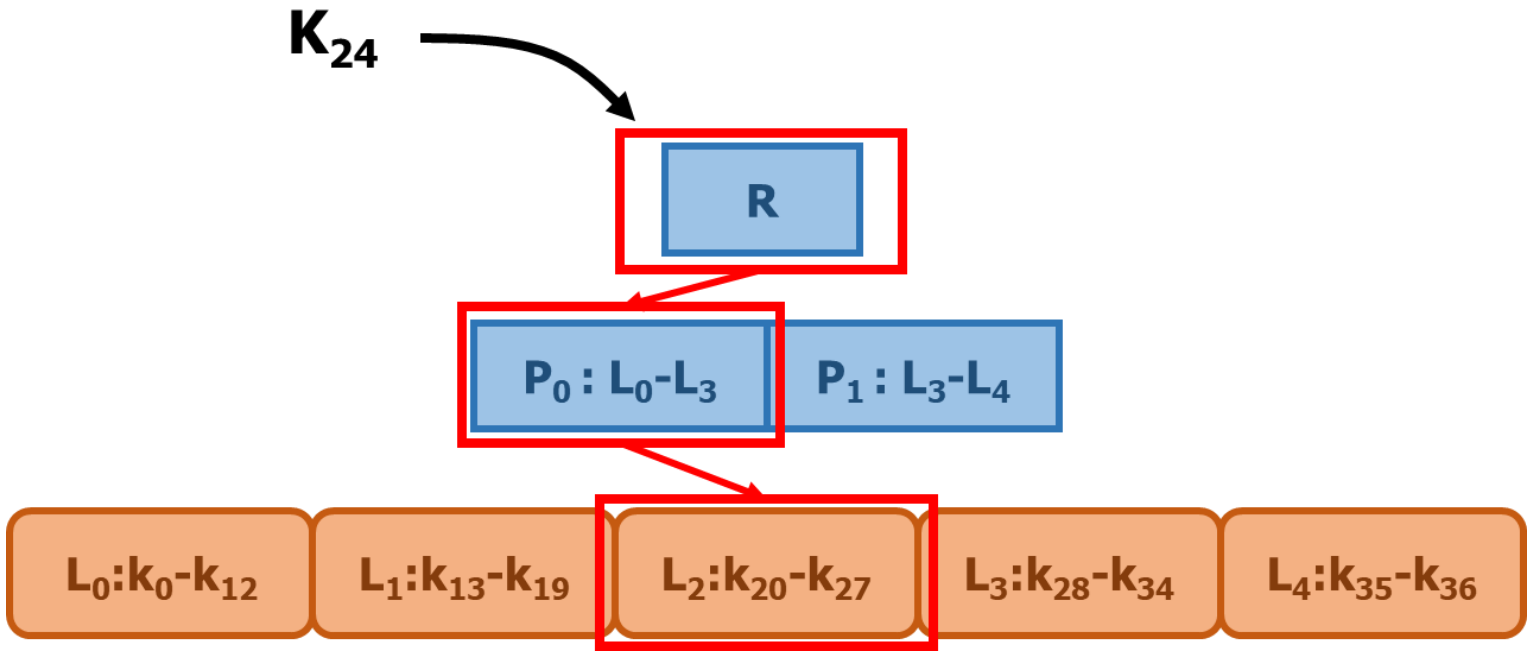
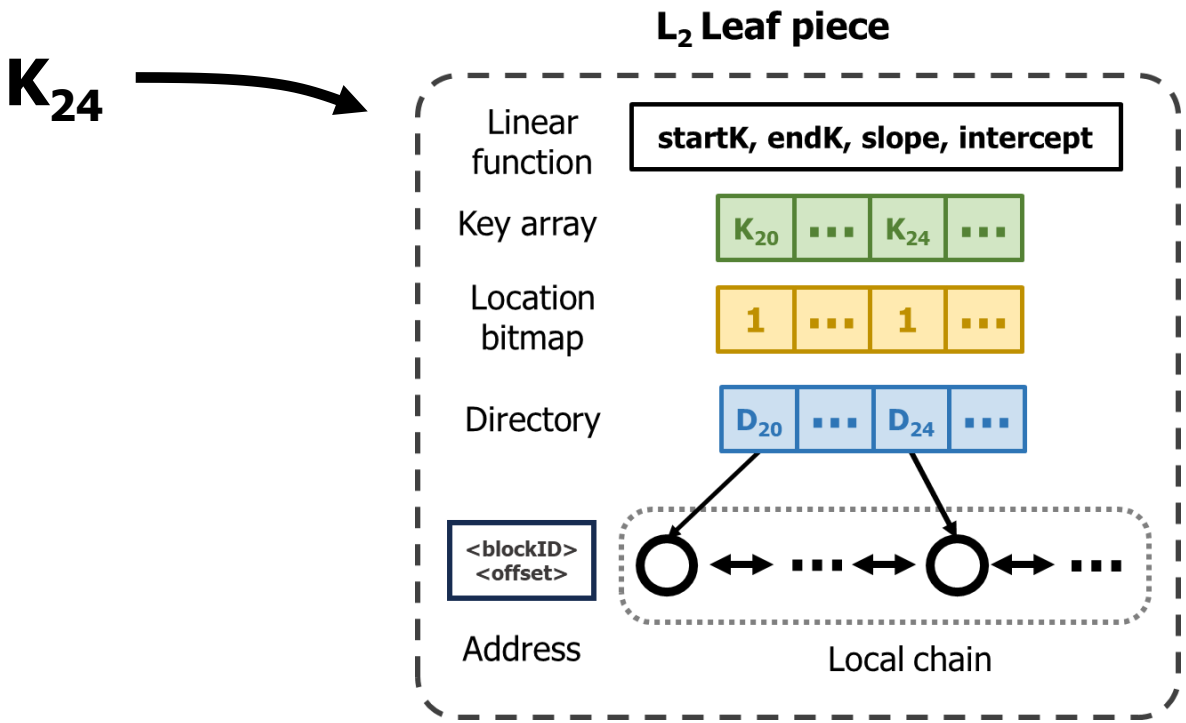


Query Processing

- Point Query

  2. Locate **K** in the piece

     Predict the position of **K**

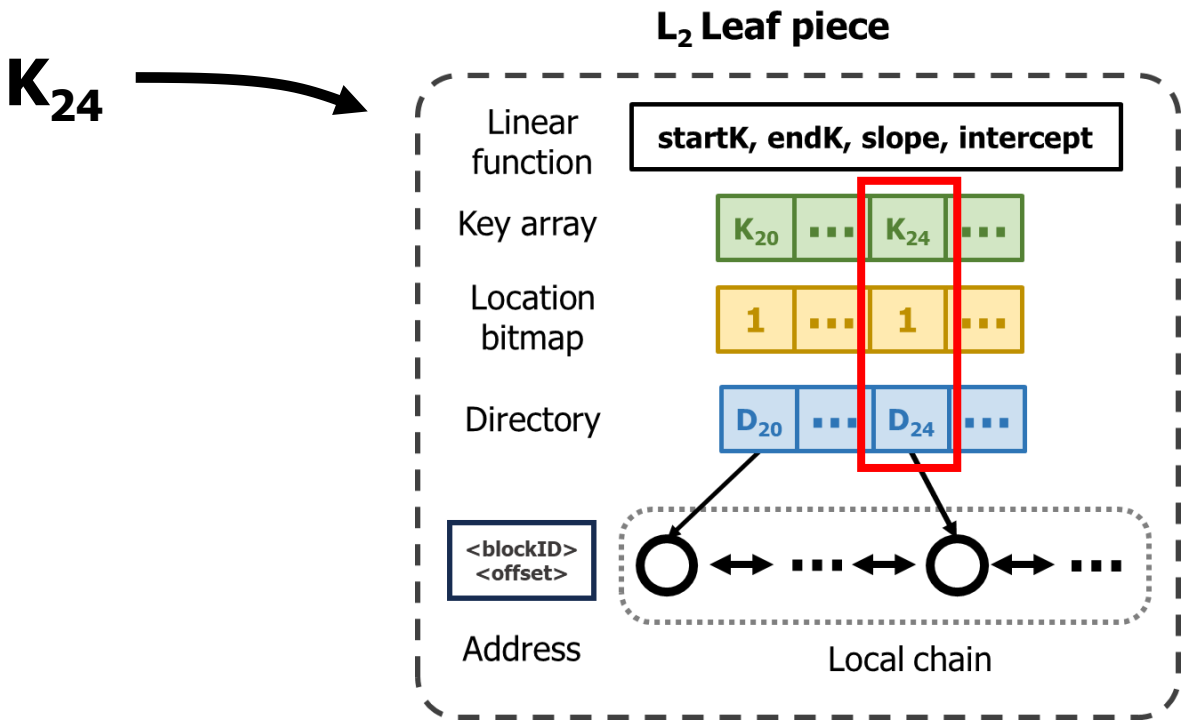


Query Processing

- 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

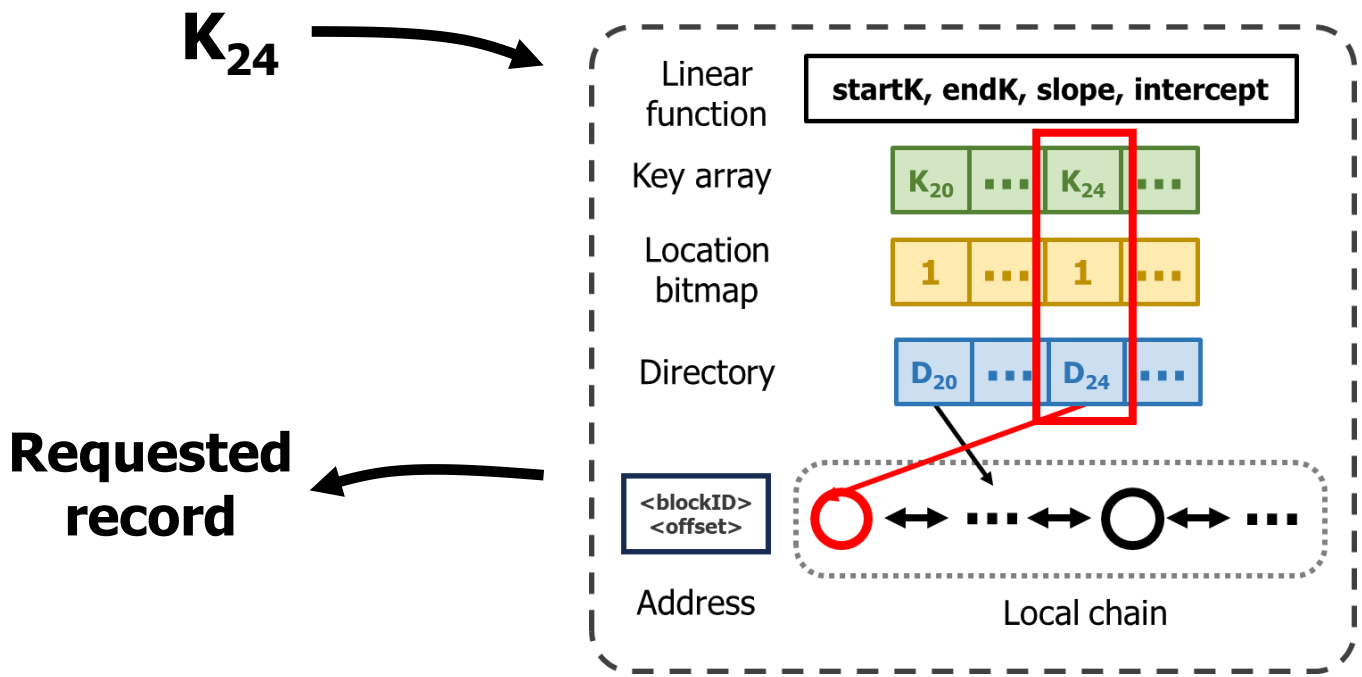


Query Processing

- Point Query

  3. Retrieve the data record and update the adaptive LRU

     Record can be directly accessed using local chain or address

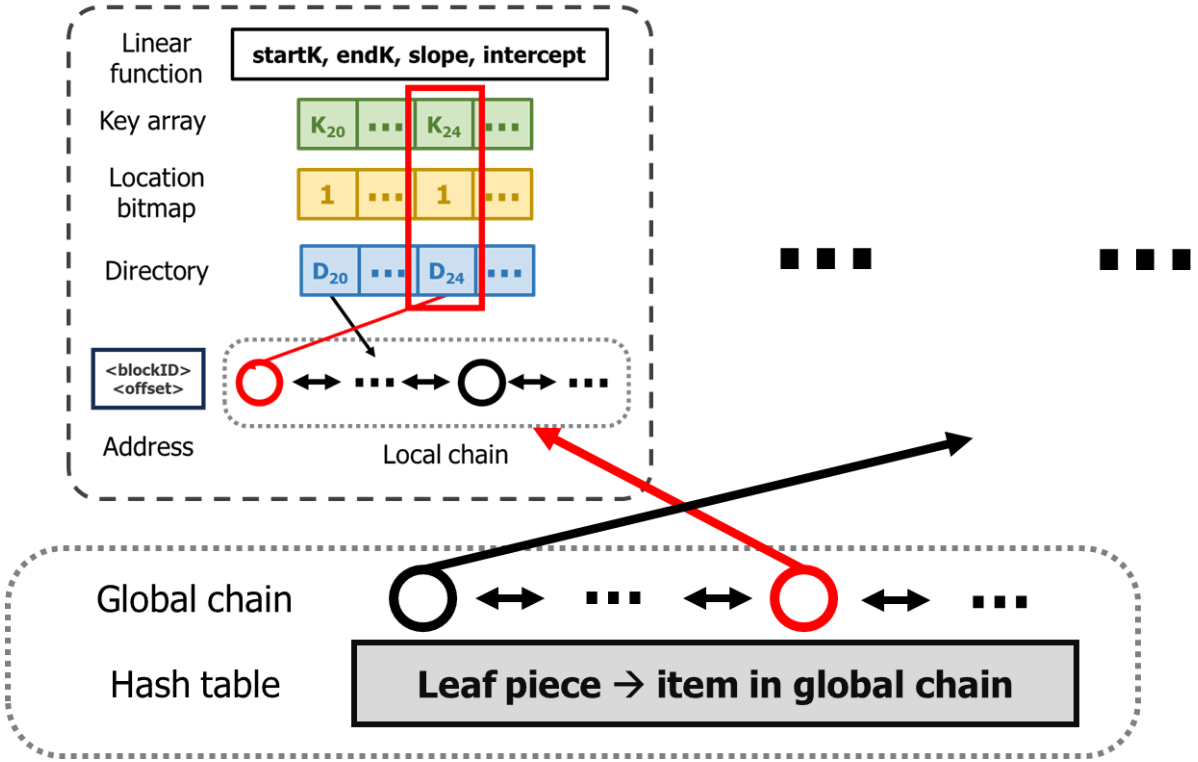


Query Processing

- 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

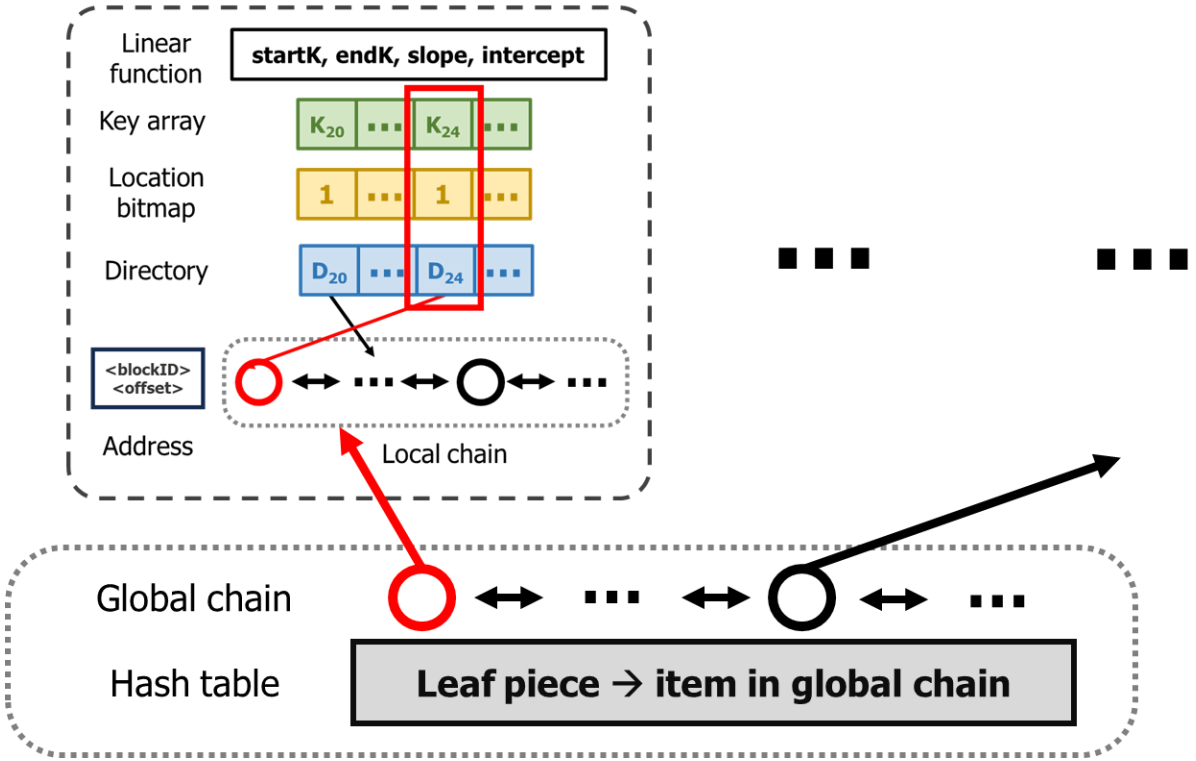


Query Processing

- Point Query

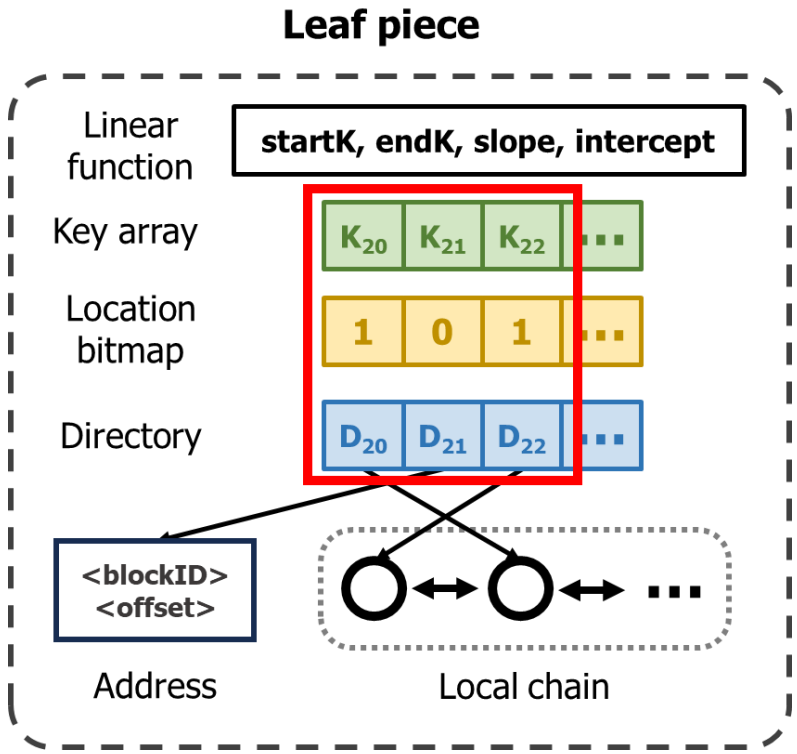
  3. Retrieve the data record and update the adaptive LRU

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



Query Processing

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

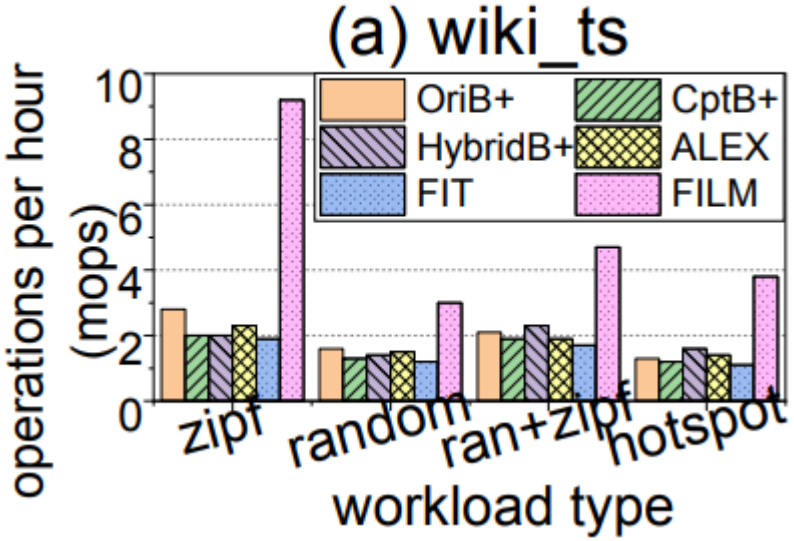


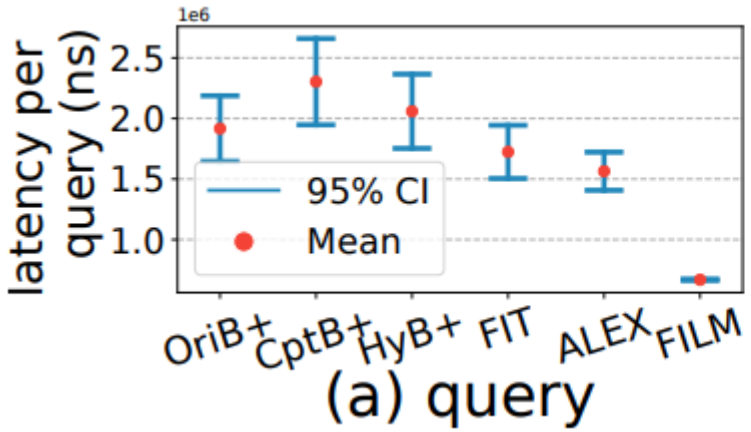
Experiments

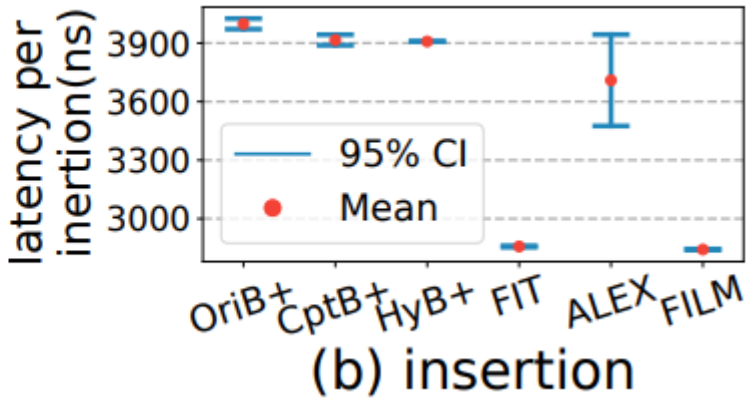
- Baselines and Experiment Setup
  - Comparison(Base Line) : B+tree, HybridB+tree, CptB+tree, Alex, Fitting-Tree
  - Datasets : wiki_ts, books, astro_a, synthetic, YCSB (64bit Key, 128Byte Value)
  - Workload : Zipfian, Hotspot, Random, Zipfian+Random
  - Spec :
    - 3.6GHz Intel CPU with 256KB L1 cache
    - 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)





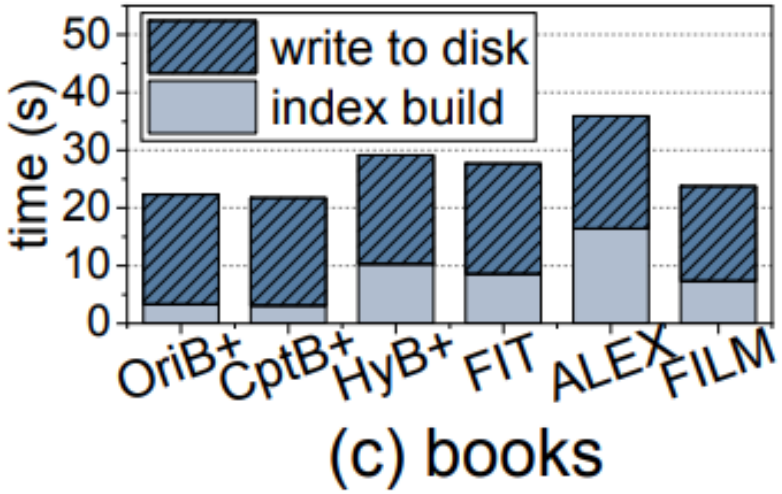


FILM has a 2-5 times advantage over base line in terms of insertion and query performance.

Film also has the lowest latency and more stable performance.

Experiments

- Comparison with Baselines
  - Index construction



(c) books

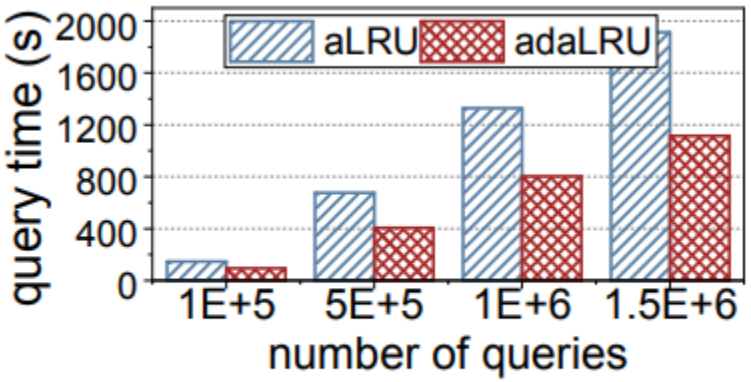
The learned index has advantages over traditional indexes in memory usage, but correspondingly, it has disadvantages in build time (about 2.2~2.5 times).

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



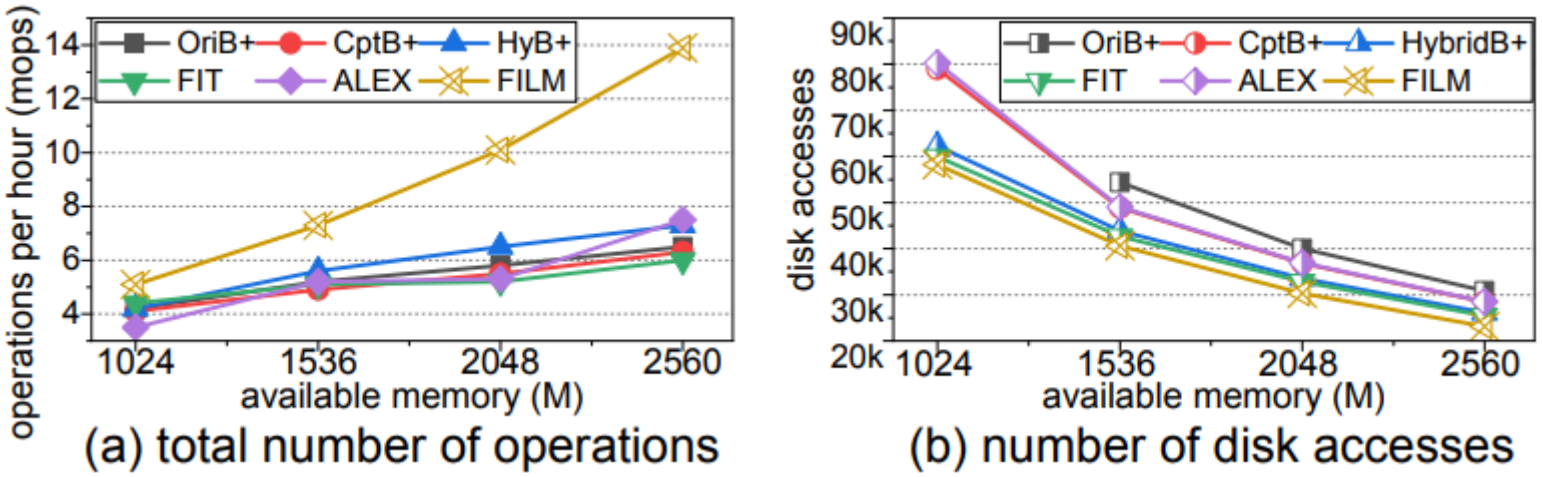
(a) aLRU vs. adaptive LRU

(b) adaB+tree vs. FILM

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

Experiments

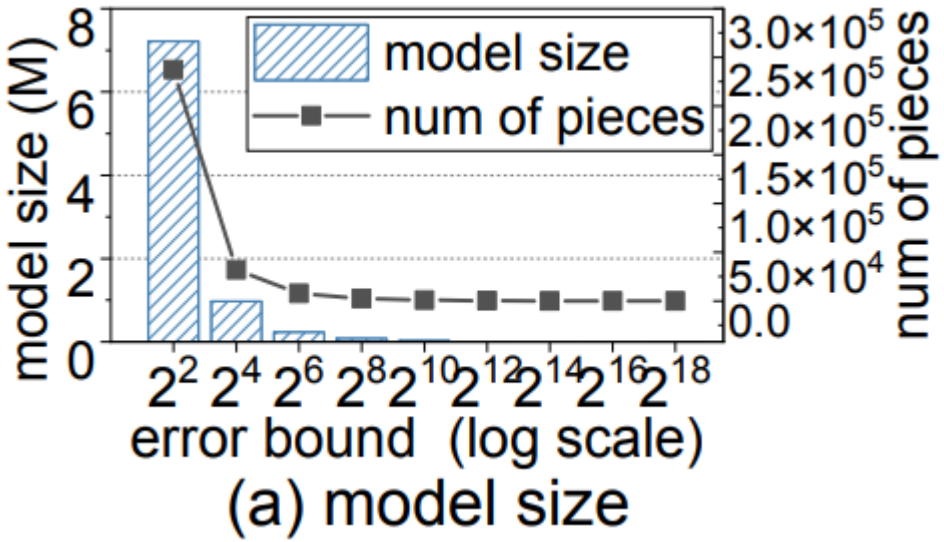
- Study of Environment Parameters
  - Available memory(4GB wiki_ts dataset, Zipfian workload)



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

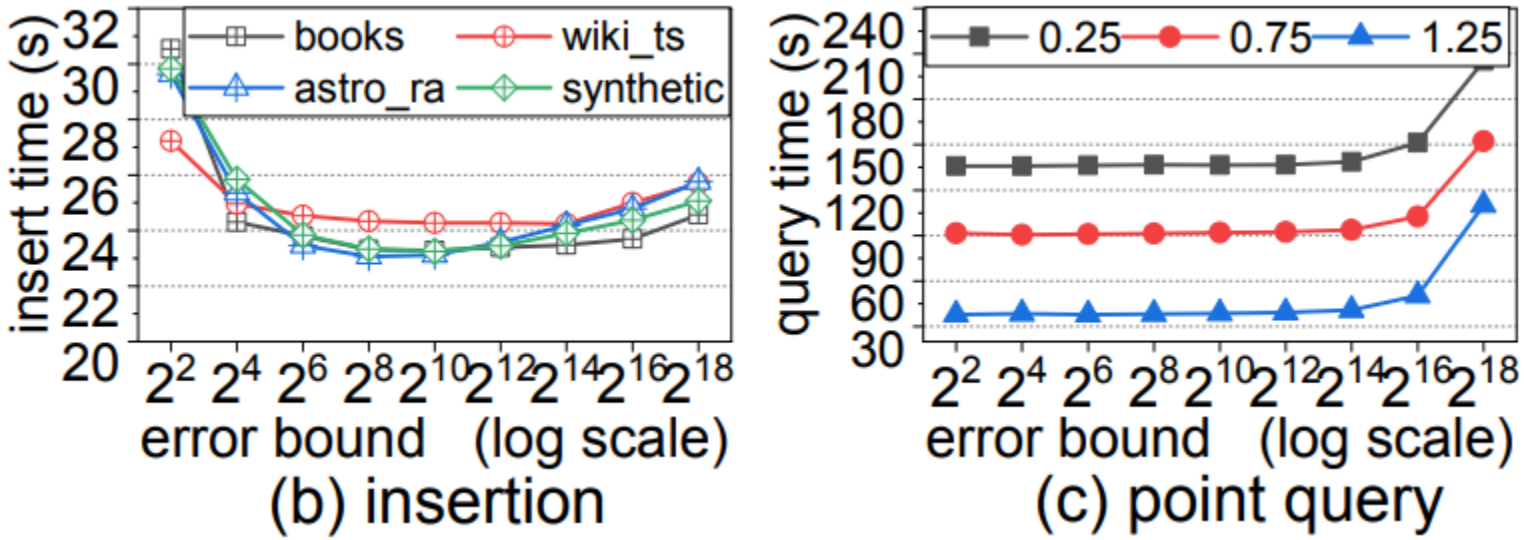


(a) model size

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

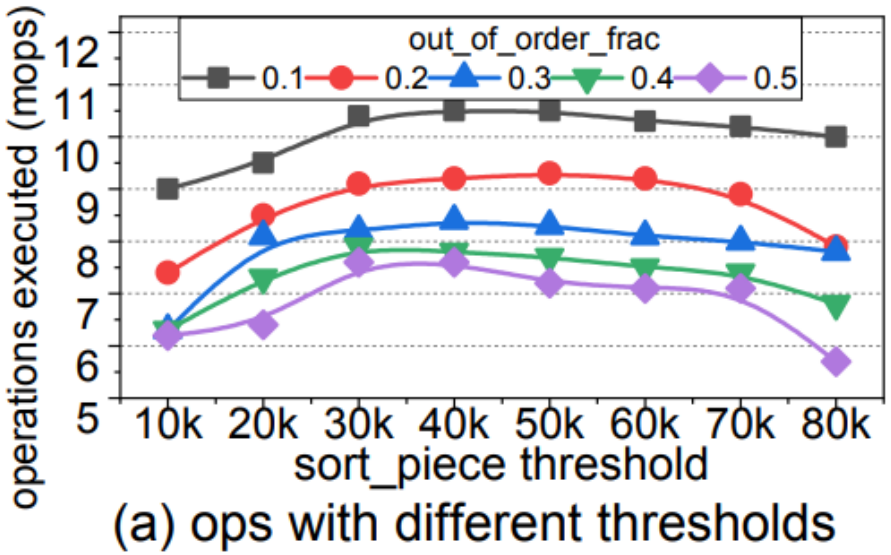
- Sensitivity to Data and Model Parameters
  - Error bound ε



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