From WiscKey to Bourbon: A Learned Index for Log-Structured Merge Trees

Yifan Dai, Yien Xu, Aishwarya Ganesan, Ramnatthan Alagappan,
Brian Kroth, Andrea Arpaci-Dusseau and Remzi Arpaci-Dusseau

Data Lookup

Data lookup is important in systems

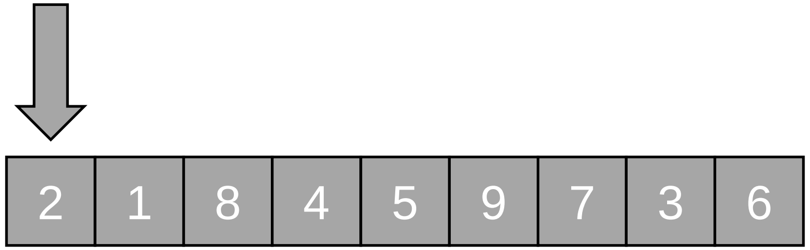
How do we perform a lookup given an array of data?

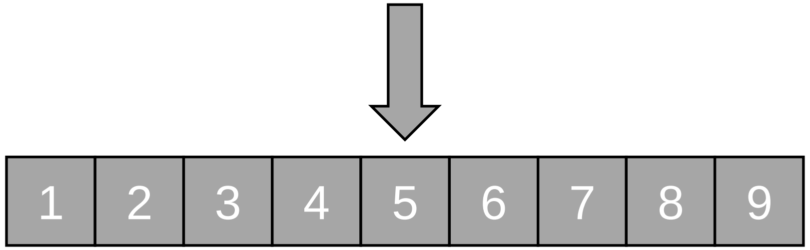
- Linear search

What if the array is sorted?

- Binary search

What if the data is huge?





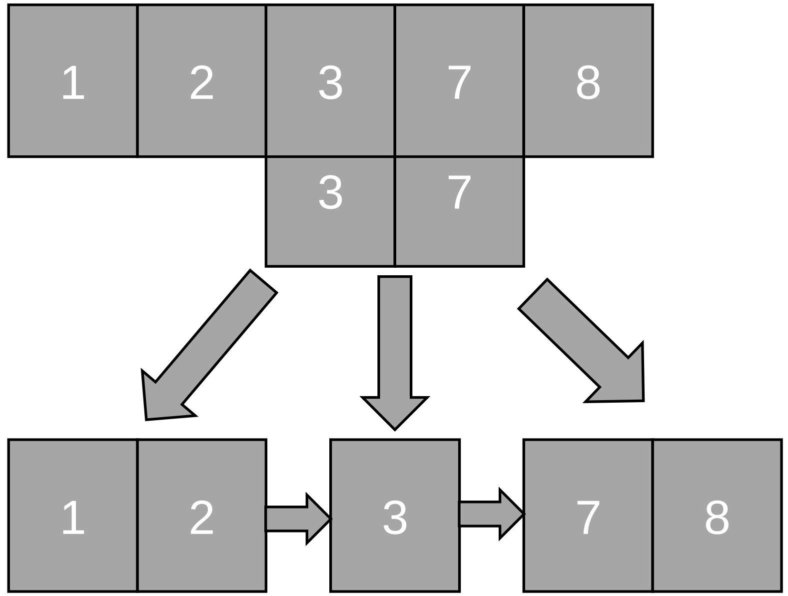
Data Structures to Facilitate Lookups

Assume sorted data

Traditional solution: build specific data structures for lookups

- B-Tree, for example
- Record the position of the data

What if we know the data beforehand?



Bring Learning to Indexing

Lookups can be faster if we know the distribution

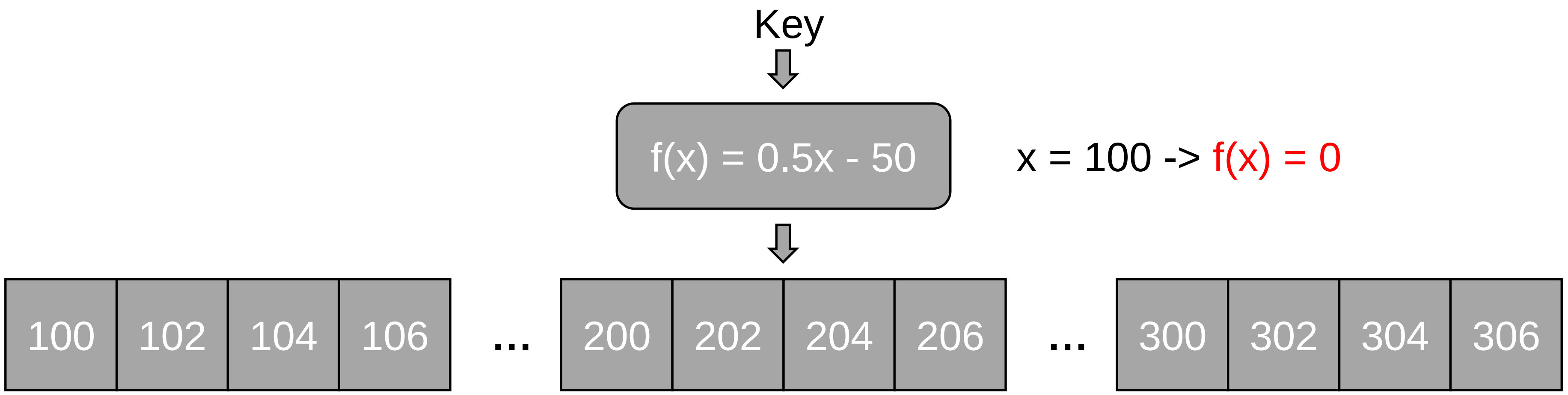
- The model f(•) learns the distribution

Leaned Indexes

Time Complexity – O(1) for lookups

Space Complexity – O(1)

- Only 2 floating points – slope + intercept



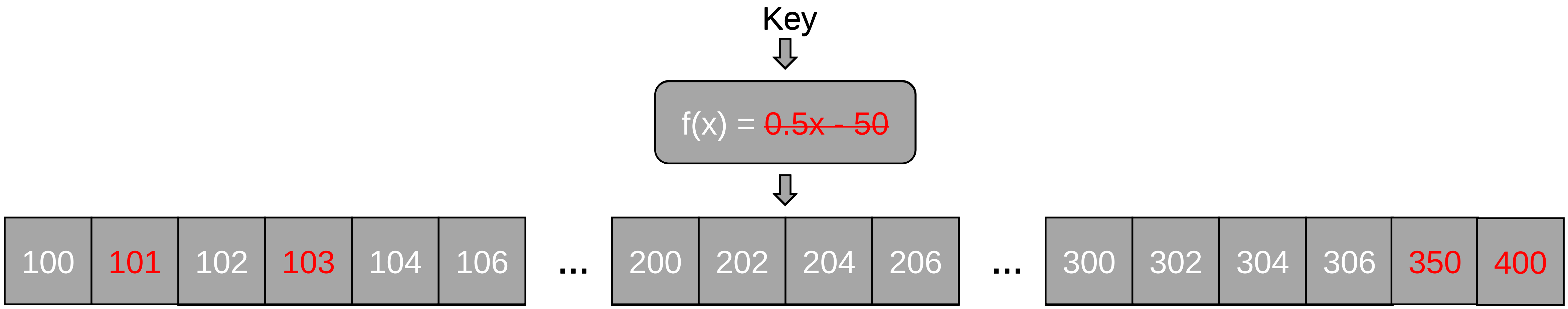
Kraska et al. The Case for Learned Index Structures. 2018

Challenges to Learned Indexes

How to efficiently support insertions/updates?

- Data distribution changed
- Need re-training, or lowered model accuracy

How to integrate into production systems?

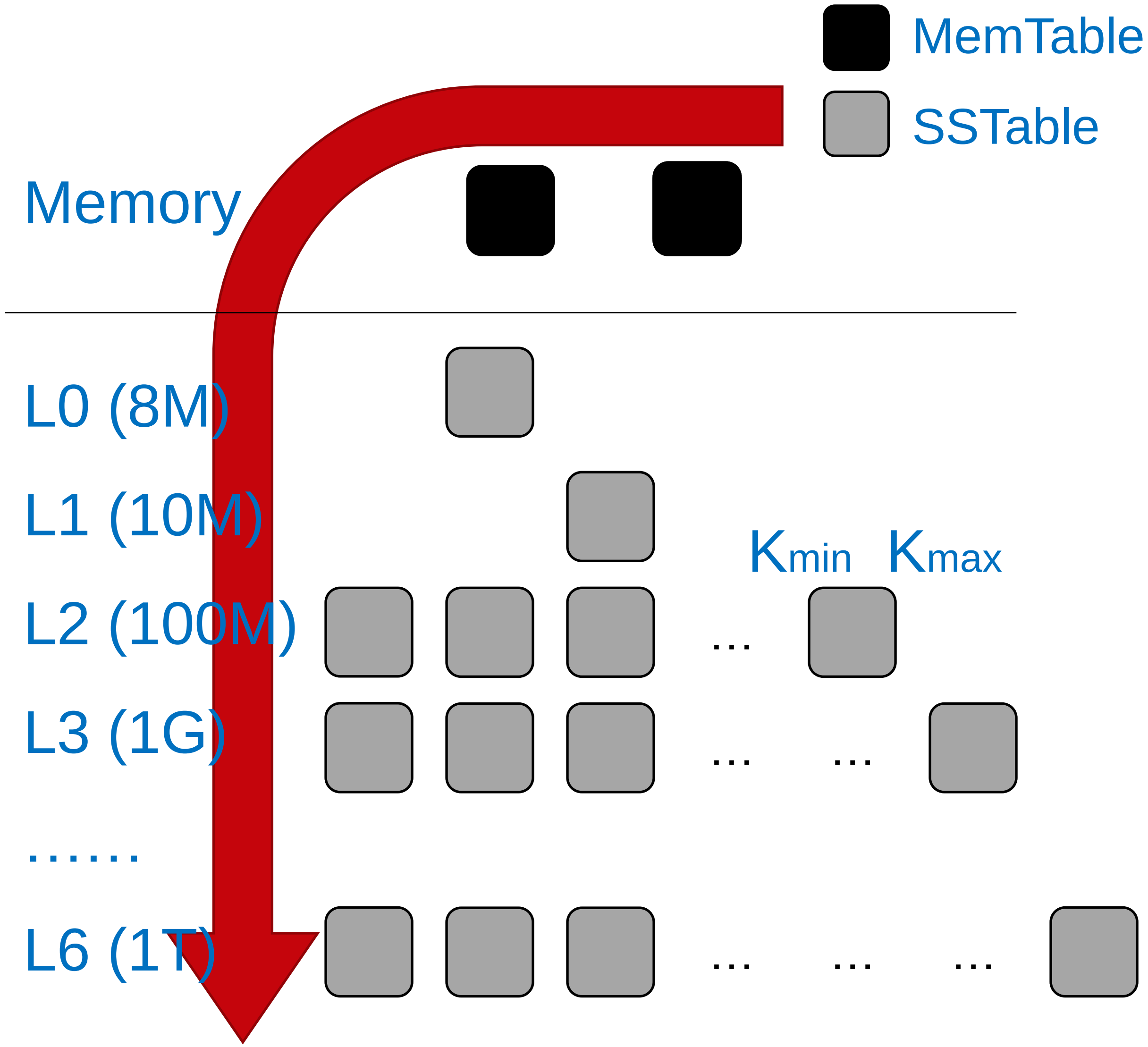


Bourbon

- Bourbon
  - A Learned index for LSM-trees
  - Built into production system (WiscKey)
  - Handle writes easily
- LSM-tree fits learned indexes well
  - Immutable SSTables with no in-place updates
- Learning guidelines
  - How and when to learn the SSTables
- Cost-Benefit Analyzer
  - Predict if a learning is beneficial during runtime
- Performance improvement
  - 1.23x – 1.78x for read-only and read-heavy workloads
  - ~1.1x for write-heavy workloads

LevelDB

- Key-value store based on LSM
  - 2 in-memory tables
  - 7 levels of on-disk SSTables (files)
- Update/Insertion procedure
  - Buffered in MemTables
  - Merging compaction
  - From upper to lower levels
  - No in-place updates to SSTables
- Lookup procedure
  - From upper to lower levels
  - Positive/Negative internal lookups



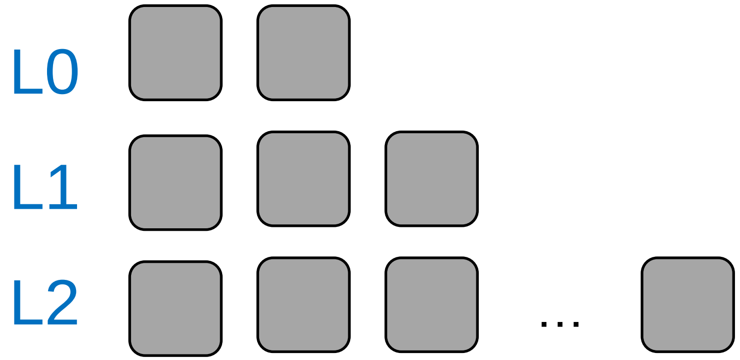
Learning Guidelines

Learning at SSTable granularity

- No need to update models
- Models keep a fixed accuracy

Factors to consider before learning:

1. Lifetime of SSTables
   - How long a model can be useful
2. Number of Lookups into SSTables
   - How often a model can be useful



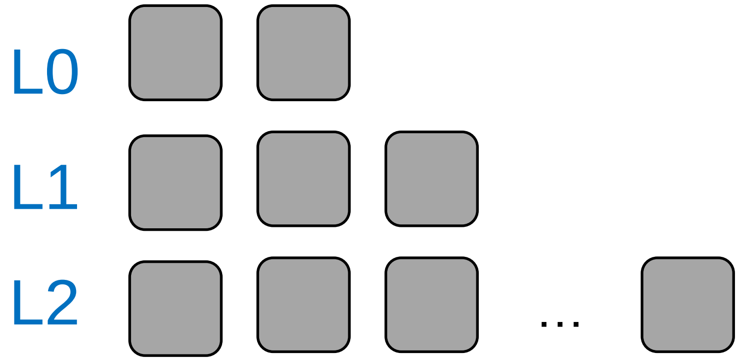
Learning Guidelines

1. Lifetime of SSTables

How long a model can be useful

Experimental results

Under 15Kops/s and 50% writes
Average lifetime of L0 tables: 10 seconds
Average lifetime of L4 tables: 1 hour
A few very short-lived tables: < 1 second



Learning guideline 1: Favor lower level tables

Lower level files live longer

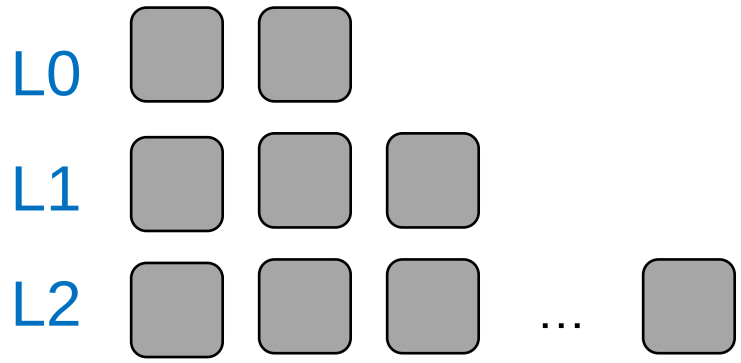
Learning guideline 2: Wait shortly before learning

Avoid learning extremely short-lived tables

Learning Guidelines

2. Number of Lookups into SSTables

    How often a model can be useful



Affected by various factors

    Depending on workload distribution, load order, etc.

    Higher level files may serve more internal lookups

Learning guideline 3: Do not neglect higher level tables

    Models for them may be more often used

Learning guideline 4: Be workload- and data-aware

    Number of internal lookups affected by various factors

Learning Algorithm: Greedy-PLR

Greedy Piecewise Linear Regression

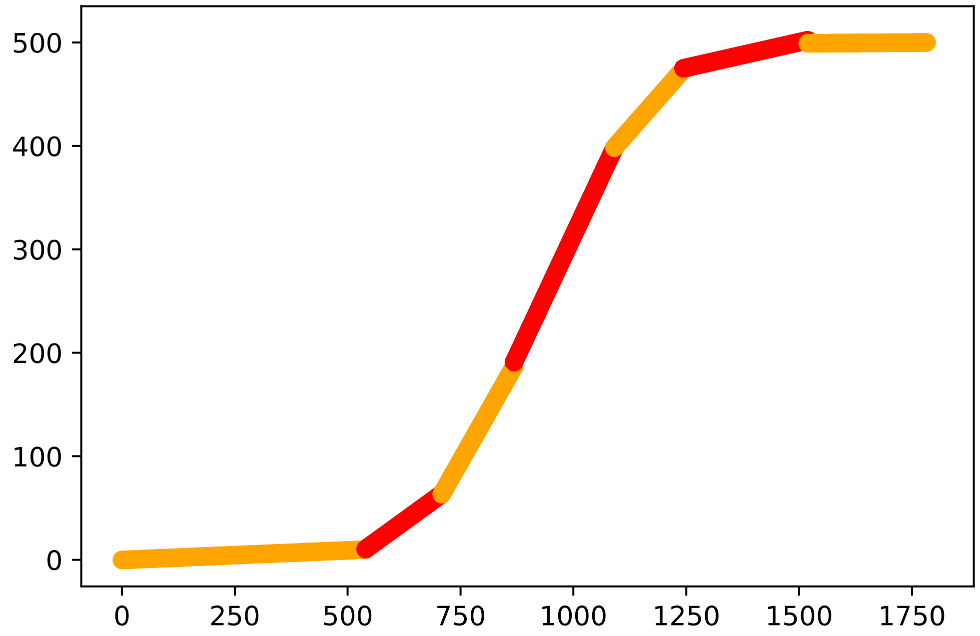
From Dataset D

Multiple linear segments $f(\cdot)$

$\forall (x, y) \in D, |f(x) - y| < error$

$error$ is specified beforehand

In bourbon, we set $error = 8$



Train complexity: O(n)

Typically ~40ms

Inference complexity: O(log #seg)

Typically <1μs

Xie et al. Maximum error-bounded piecewise linear representation for online stream approximation. 2014

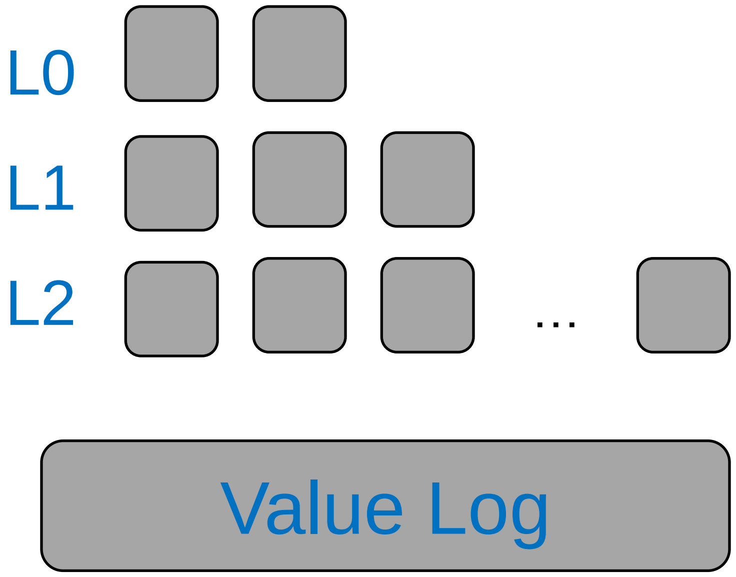
Bourbon Design

Bourbon: Build upon WiscKey

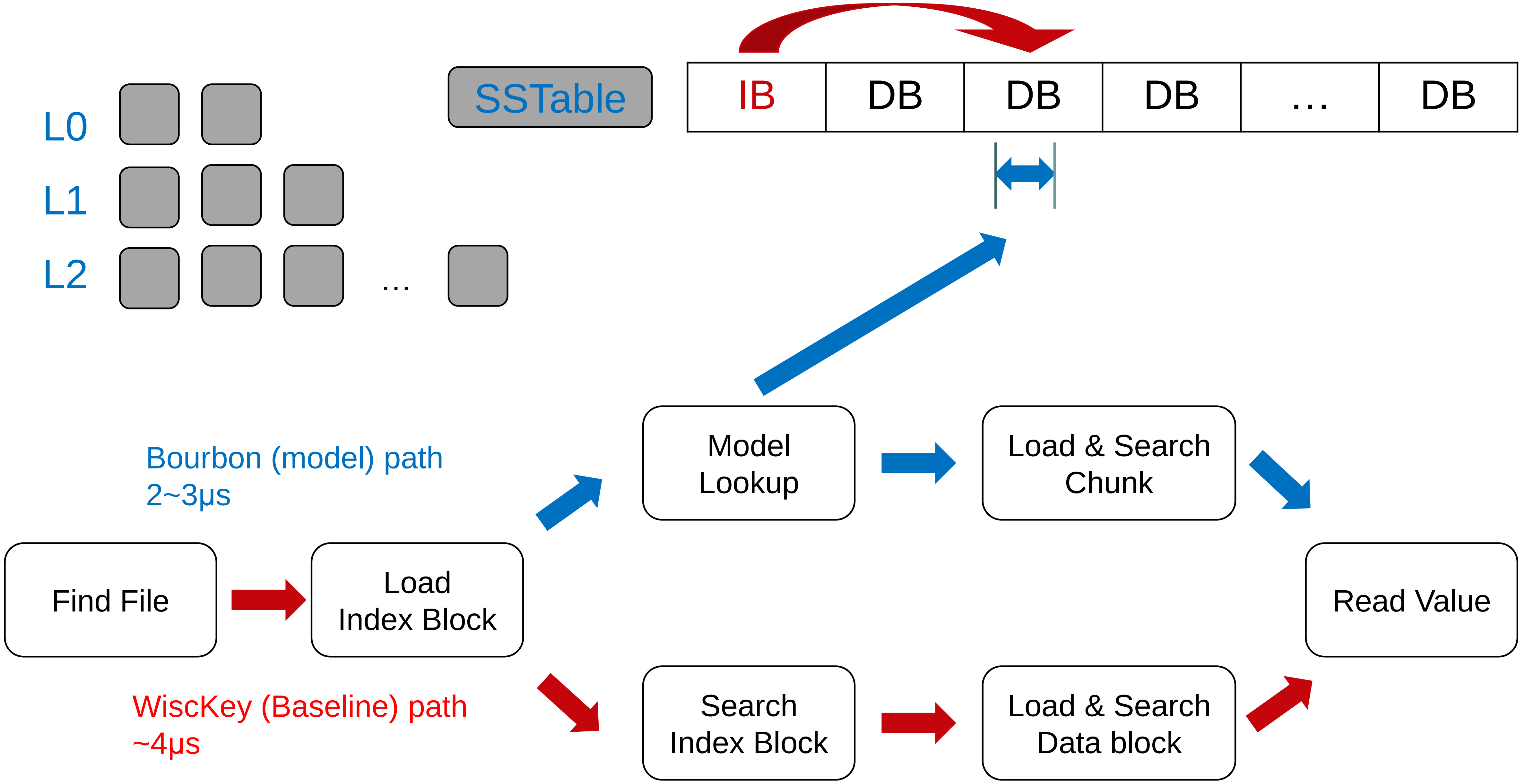
- WiscKey: key-value separation built upon LevelDB
- (Key, value_addr) pair in the LSM-tree
- A separate value log

Why WiscKey?

- Help handle large and variable sized values
- Constant-sized KV pairs in the LSM-tree
- Prediction much easier



Bourbon Design



Evaluation

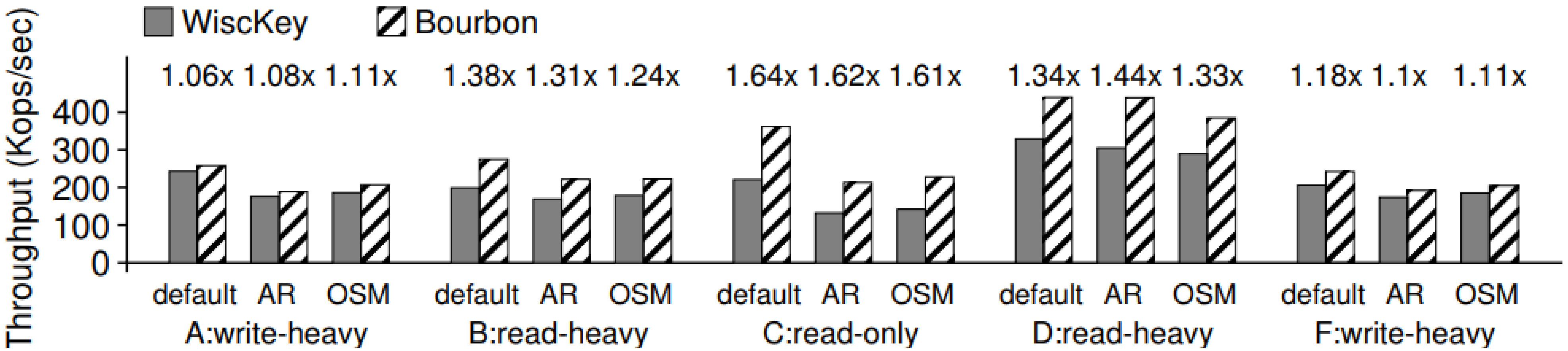
Read-only workloads: 1.23x – 1.78x

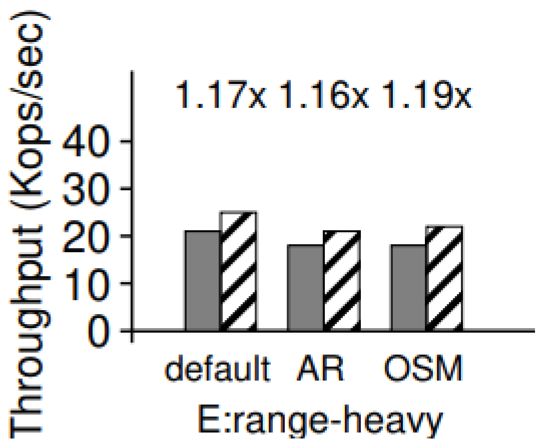
- Datasets
- Load Orders
- Request Distributions

YCSB core workloads: see graph below

SOSD & CBA effectiveness & Experiments on fast storage

- In our paper





Conclusion

Bourbon

- Integrates learned indexes into a production LSM system
- Beneficial on various workloads
- Learning guidelines on how and when to learn
- Cost-Benefit Analyzer on whether a learning is worthwhile

How will ML change computer system **mechanisms**?

- Not just policies
- Bourbon improves the lookup process with learned indexes
- What other mechanisms can ML replace or improve?
- Careful study and deep understanding are required

Thank You for Watching!

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https://research.cs.wisc.edu/wind/

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