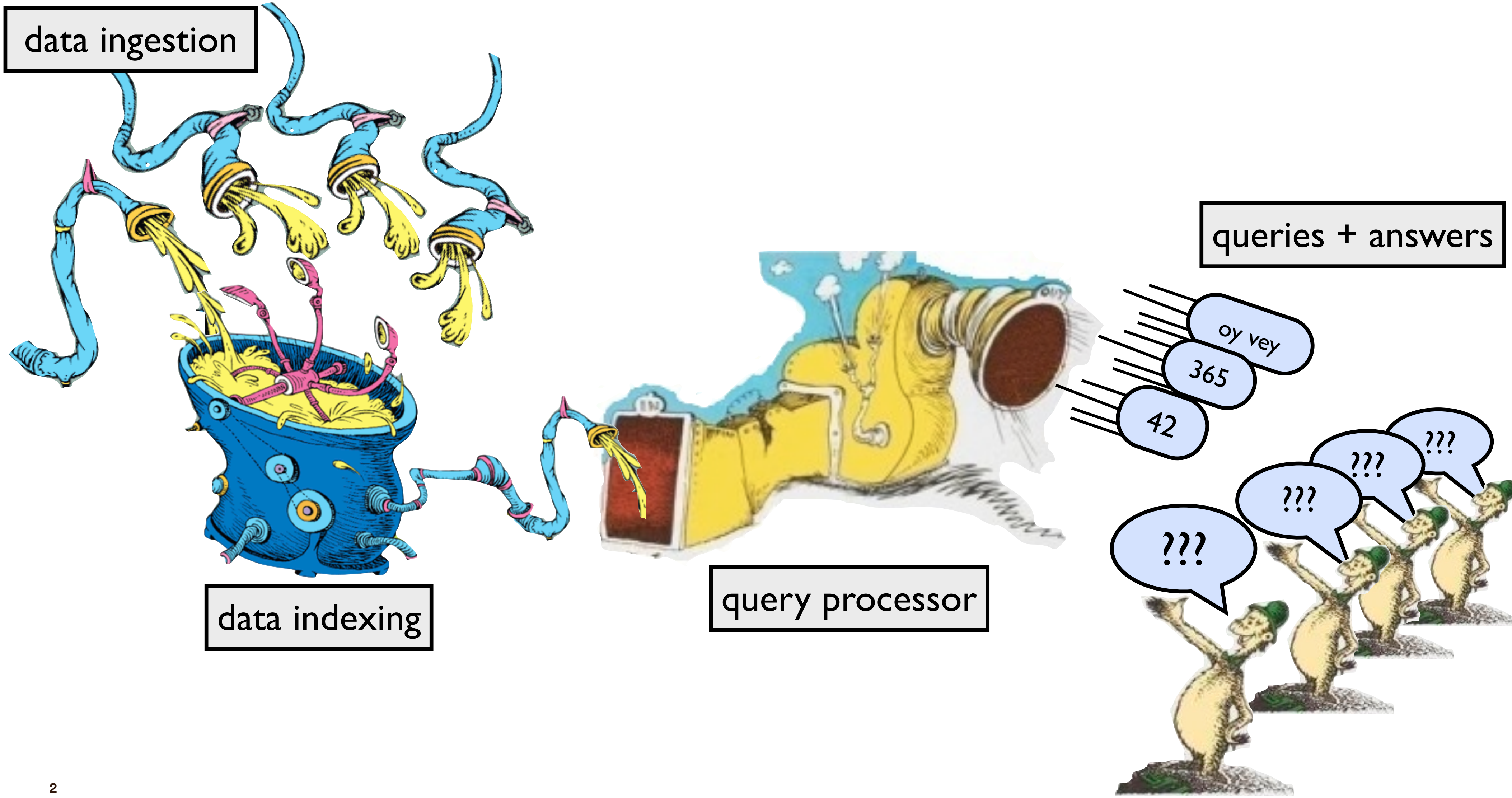
Data Structures and Algorithms for Big Databases

Michael A. Bender
Stony Brook & Tokutek

Bradley C. Kuszmaul
MIT & Tokutek



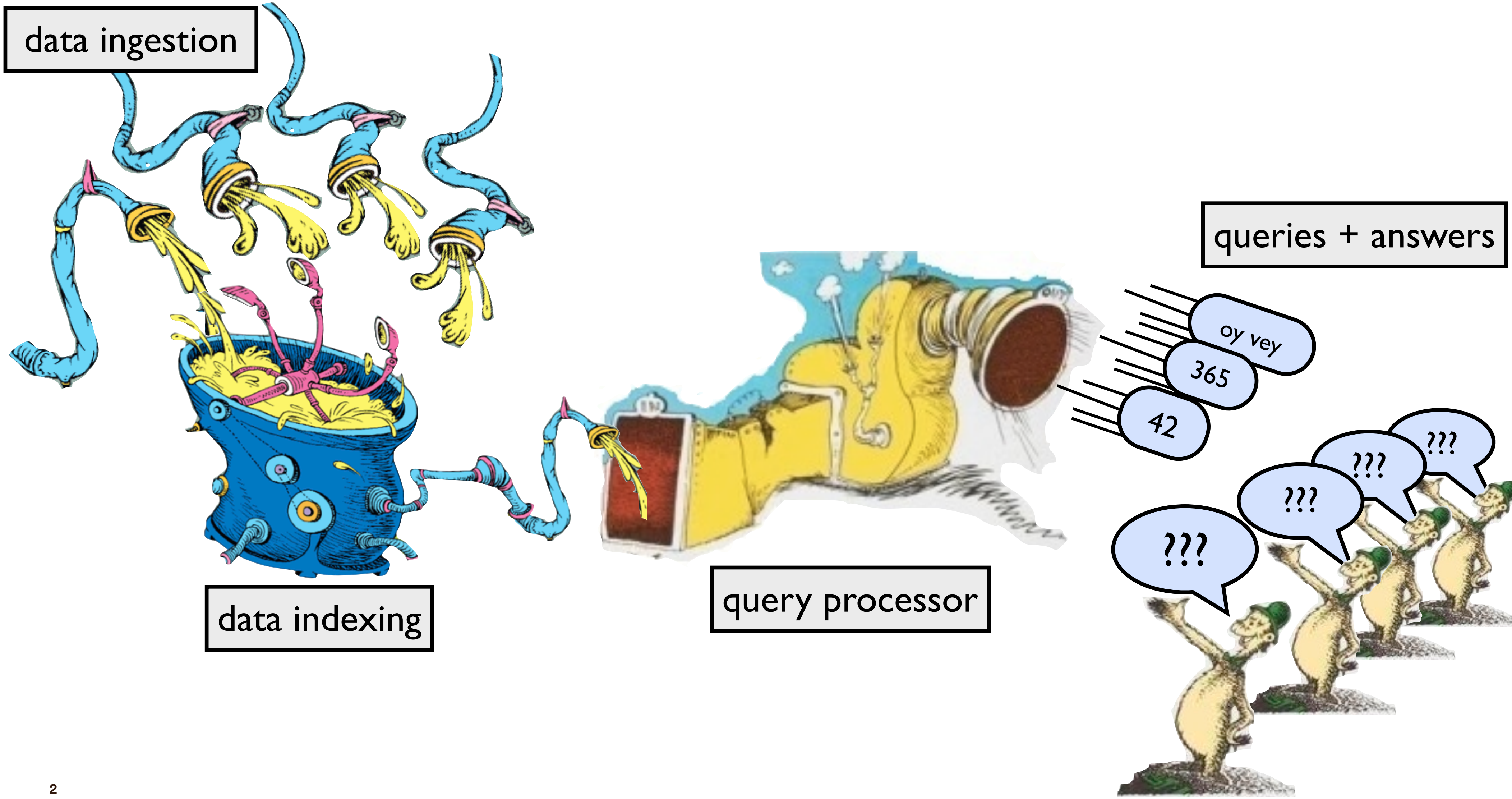
data ingestion

data indexing

query processor

queries + answers

For on-disk data, one sees funny tradeoffs in the speeds of data ingestion, query speed, and freshness of data.



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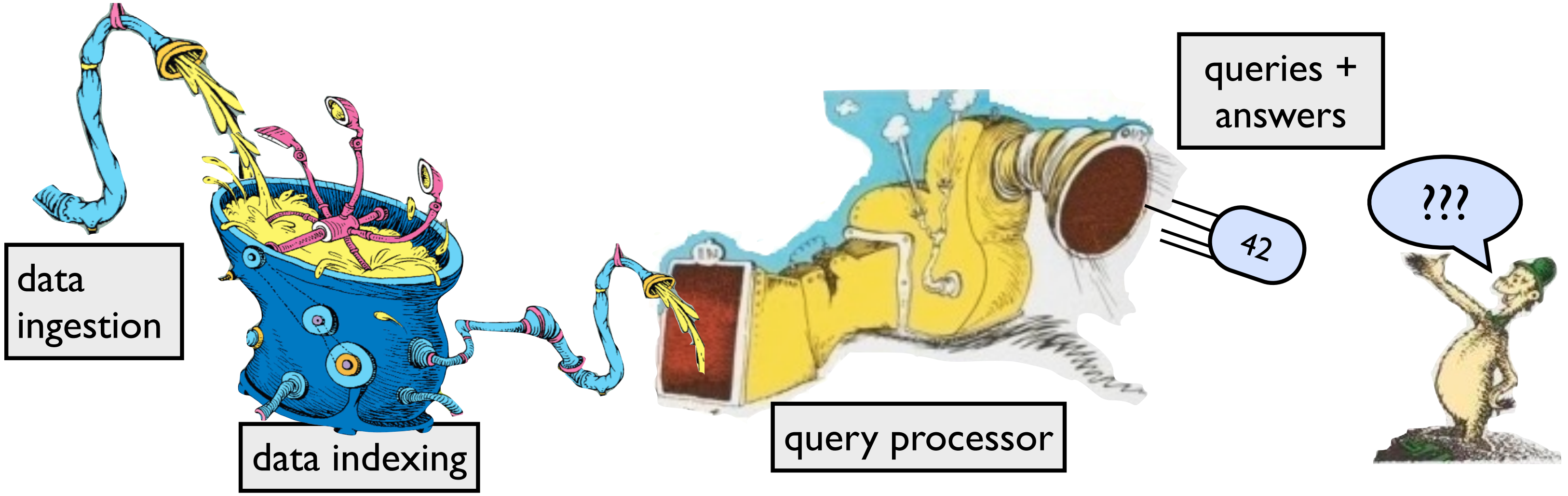
Funny tradeoff in ingestion, querying, freshness

- “I'm trying to create indexes on a table with 308 million rows. It took ~20 minutes to load the table but 10 days to build indexes on it.”
  - MySQL bug #9544



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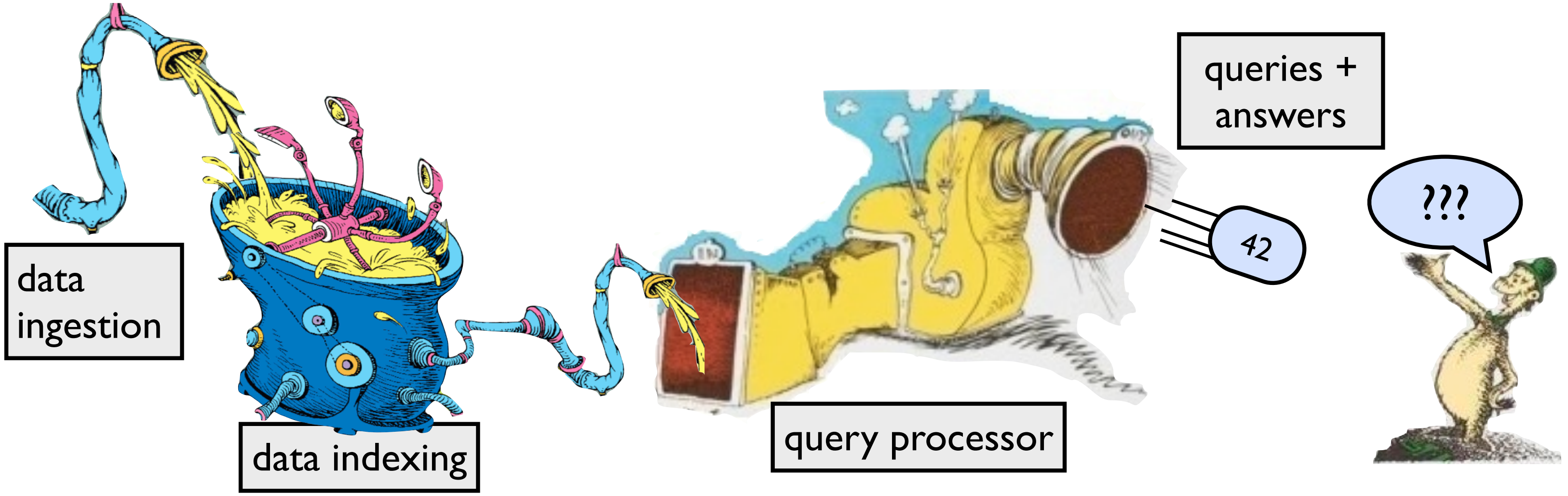

Funny tradeoff in ingestion, querying, freshness

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- “They indexed their tables, and indexed them well,
  And lo, did the queries run quick!
  But that wasn’t the last of their troubles, to tell–
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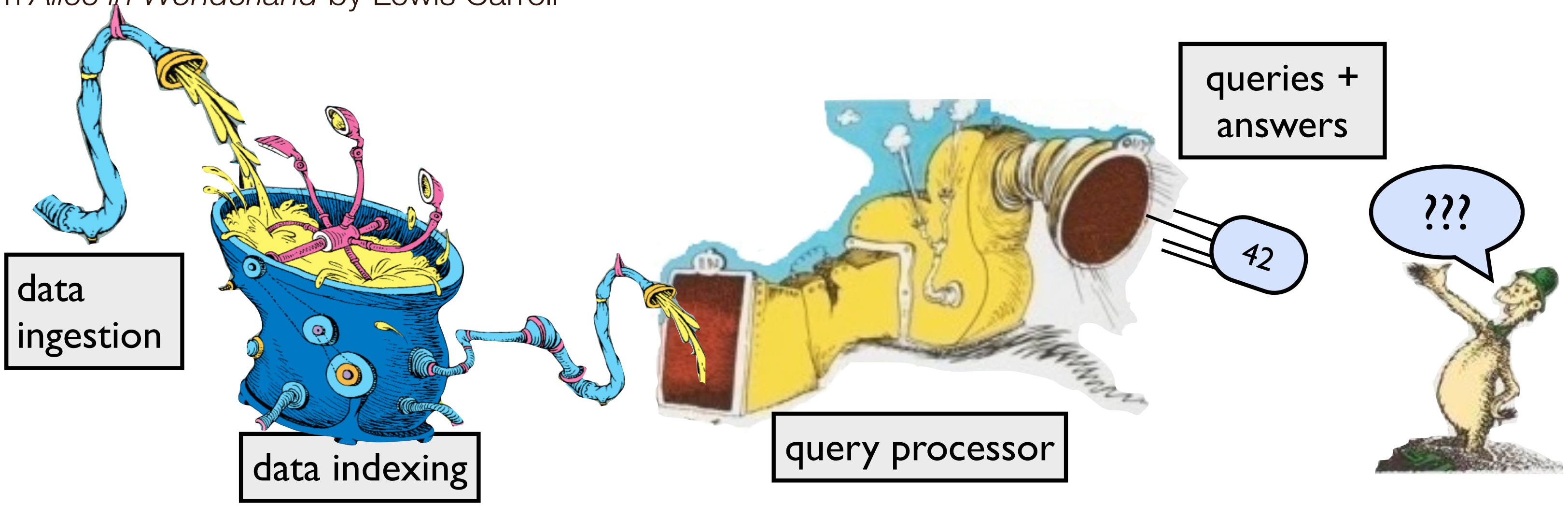
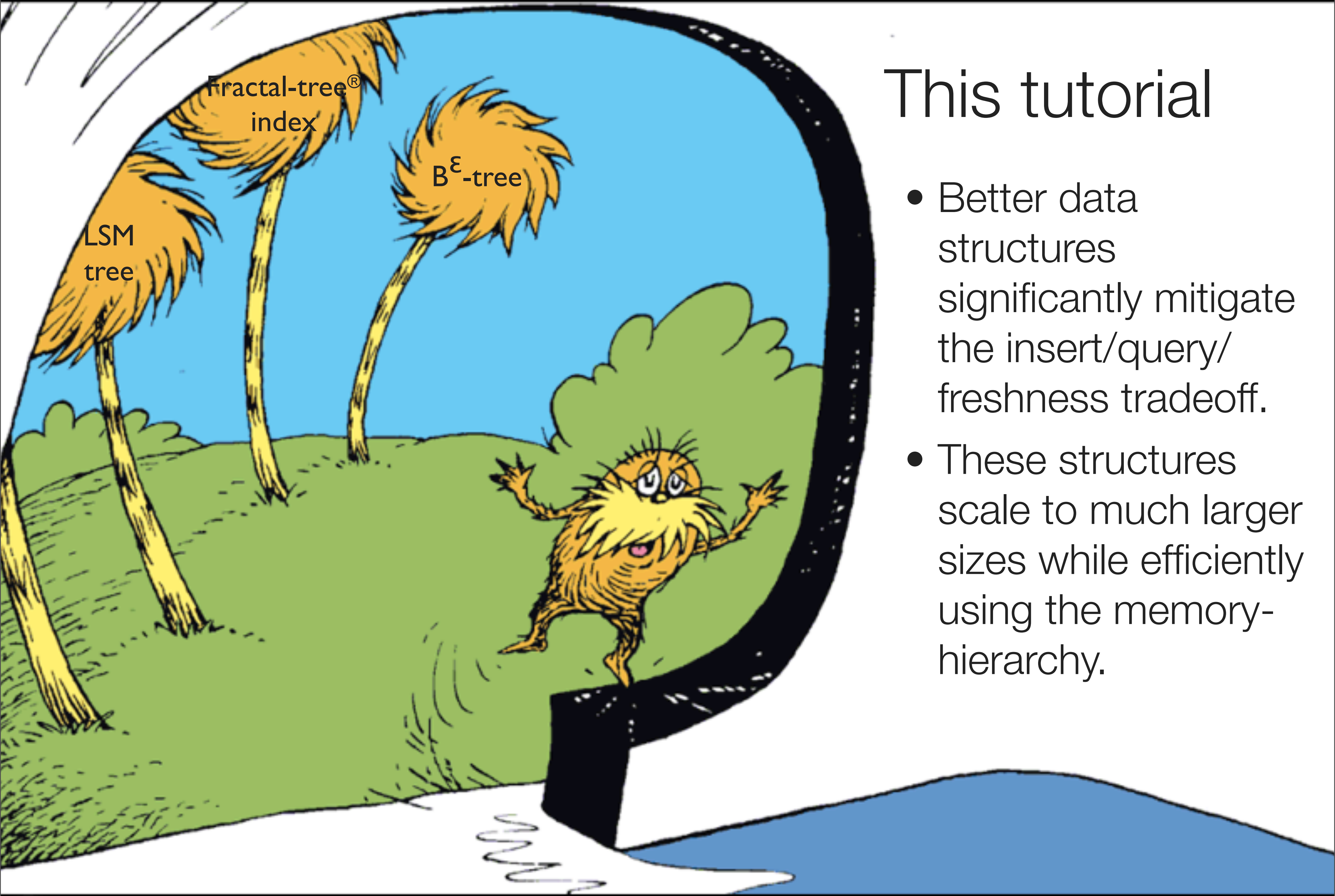




This tutorial

- Better data structures significantly mitigate the insert/query/freshness tradeoff.
- These structures scale to much larger sizes while efficiently using the memory-hierarchy.

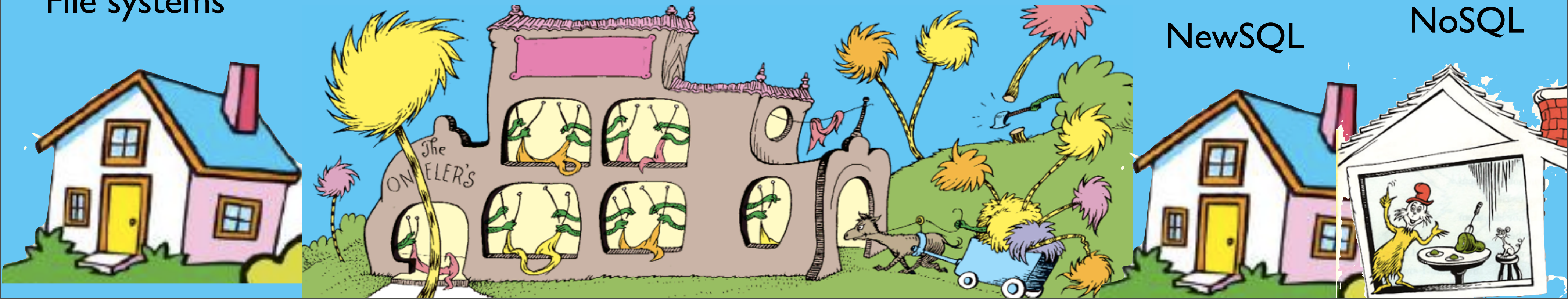
What we mean by Big Data

We don’t define Big Data in terms of TB, PB, EB.

By Big Data, we mean

- The data is too big to fit in main memory.
- We need data structures on the data.
- Words like “index” or “metadata” suggest that there are underlying data structures.
- These data structures are also too big to fit in main memory.

In this tutorial we study the underlying data structures for managing big data.



But enough about databases...

... more about us.

A few years ago we started working together on I/O-efficient and cache-oblivious data structures.

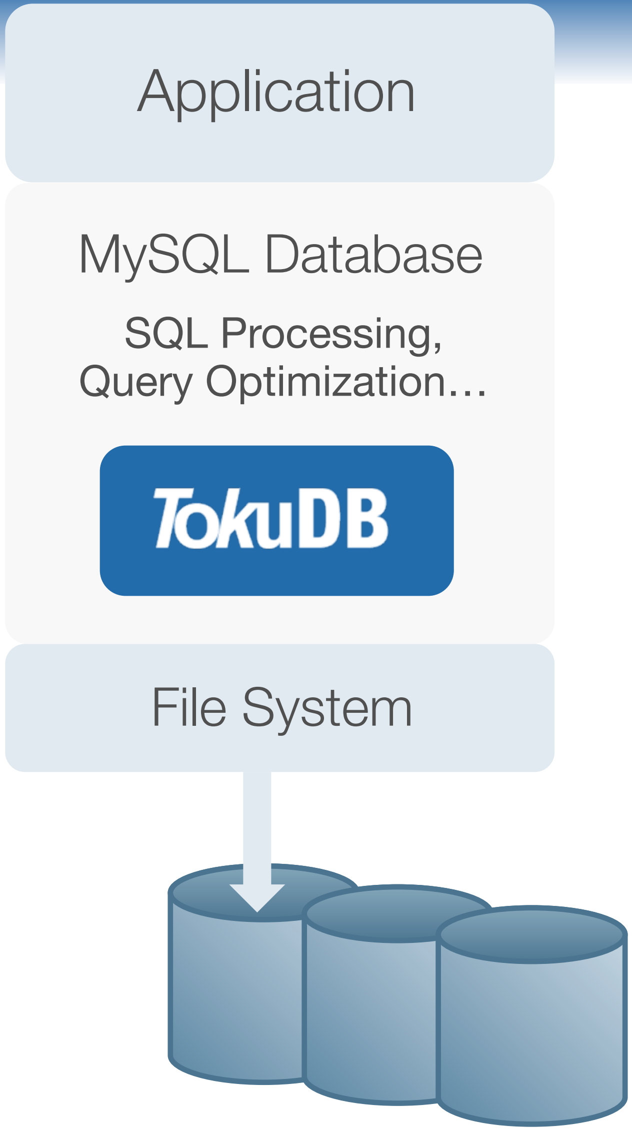
Michael

Martin

Bradley

Along the way, we started Tokutek to commercialize our research.

Storage engines in MySQL



Application

MySQL Database

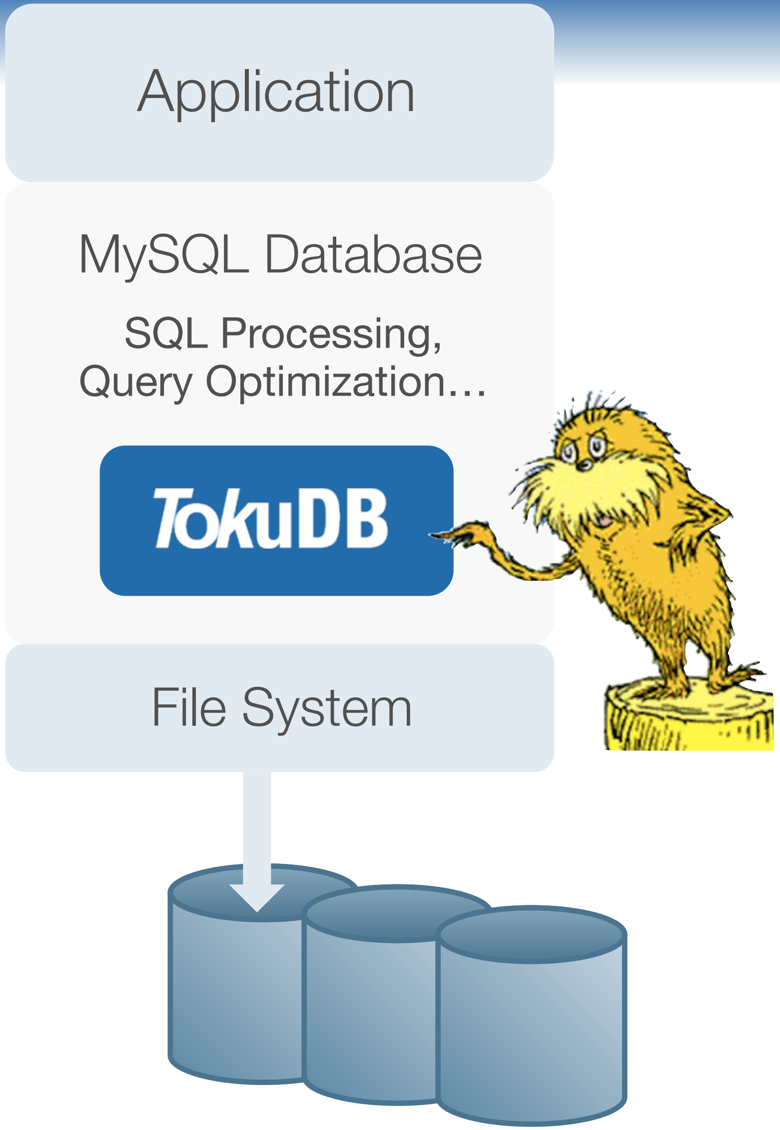
SQL Processing,
Query Optimization…

TokuDB

File System

Tokutek sells TokuDB, an ACID compliant, closed-source storage engine for MySQL.

Storage engines in MySQL



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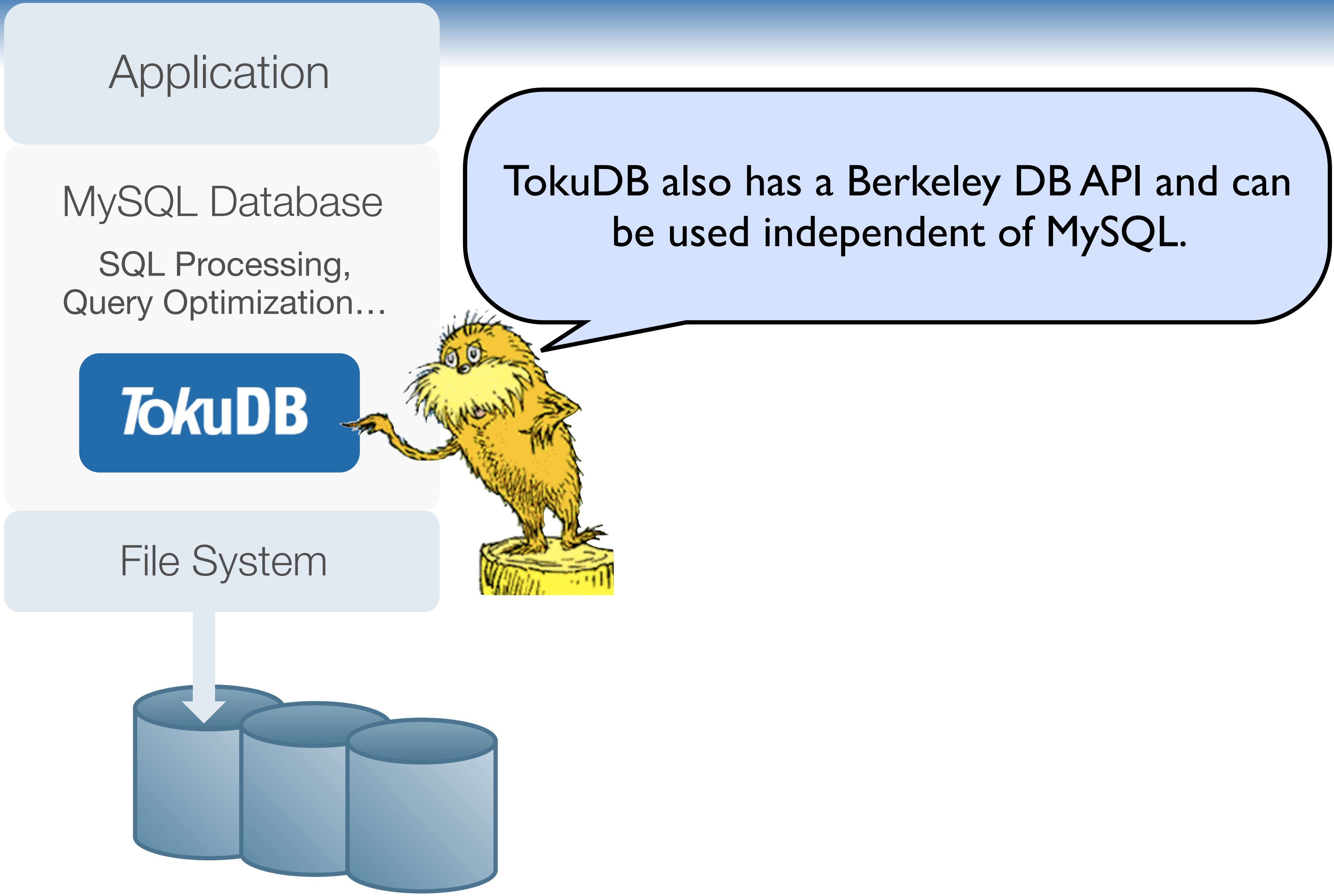

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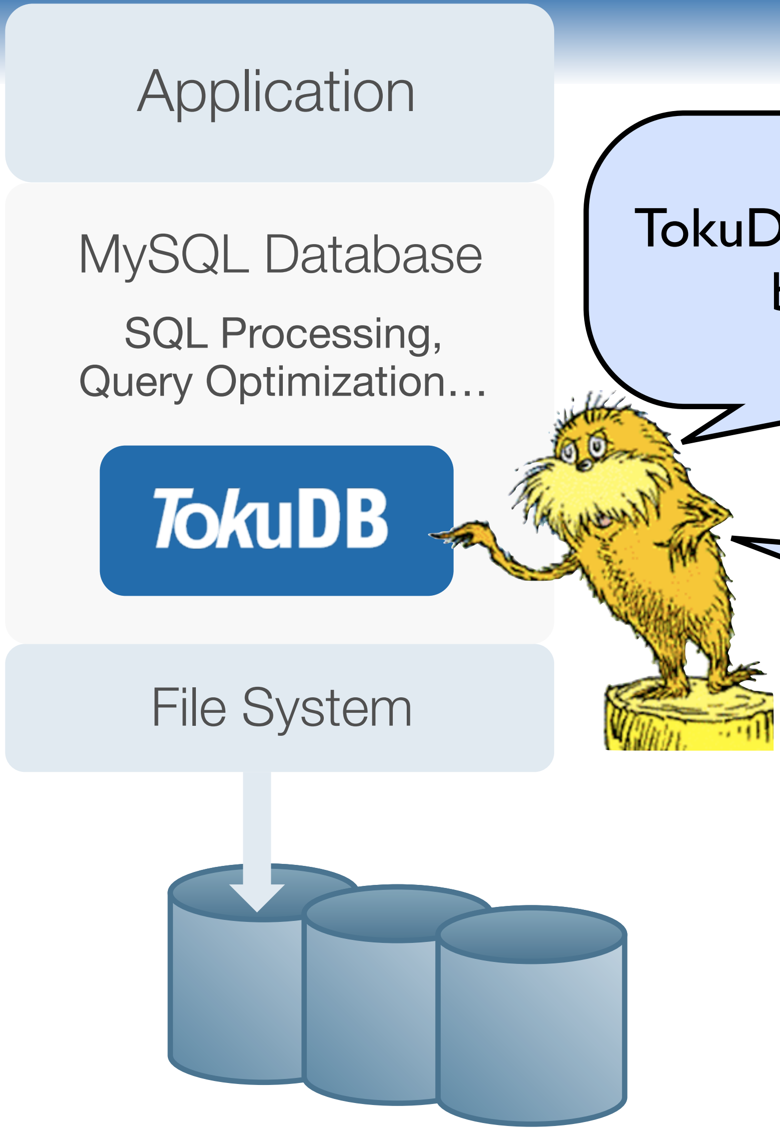

Application

MySQL Database

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TokuDB also has a Berkeley DB API and can be used independent of MySQL.

Many of the data structures ideas in this tutorial were used in developing TokuDB. But this tutorial is about data structures and algorithms, not TokuDB or any other platform.

Tokutek sells TokuDB, an ACID compliant, closed-source storage engine for MySQL.

Our Mindset

- This tutorial is self contained.
- We want to teach.
- If something we say isn’t clear to you, please ask questions or ask us to clarify/repeat something.
- You should be comfortable using math.
- You should want to listen to data structures for an afternoon.

Topics and Outline for this Tutorial

I/O model and cache-oblivious analysis.

Write-optimized data structures.

How write-optimized data structures can help file systems.

Block-replacement algorithms.

Indexing strategies.

Log-structured merge trees.

Bloom filters.

Data Structures and Algorithms for Big Data

Module 1: I/O Model and Cache-Oblivious Analysis

Michael A. Bender
Stony Brook & Tokutek

Bradley C. Kuszmaul
MIT & Tokutek

Story for Module

- If we want to understand the performance of data structures within databases we need algorithmic models for modeling I/Os.
- There’s a long history of models for understanding the memory hierarchy. Many are beautiful. Most have not found practical use.
- Two approaches are very powerful.
- That’s what we’ll present here so we have a foundation for the rest of the tutorial.

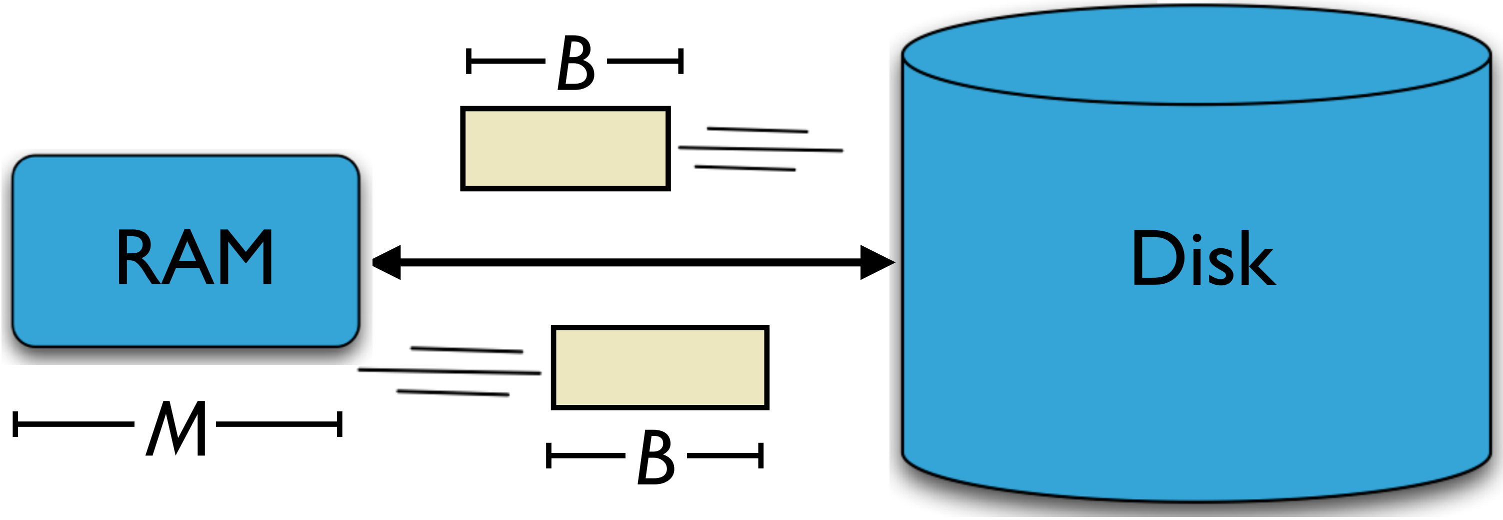
Modeling I/O Using the Disk Access Model

How computation works:

- Data is transferred in blocks between RAM and disk.
- The # of block transfers dominates the running time.

Goal: Minimize # of block transfers

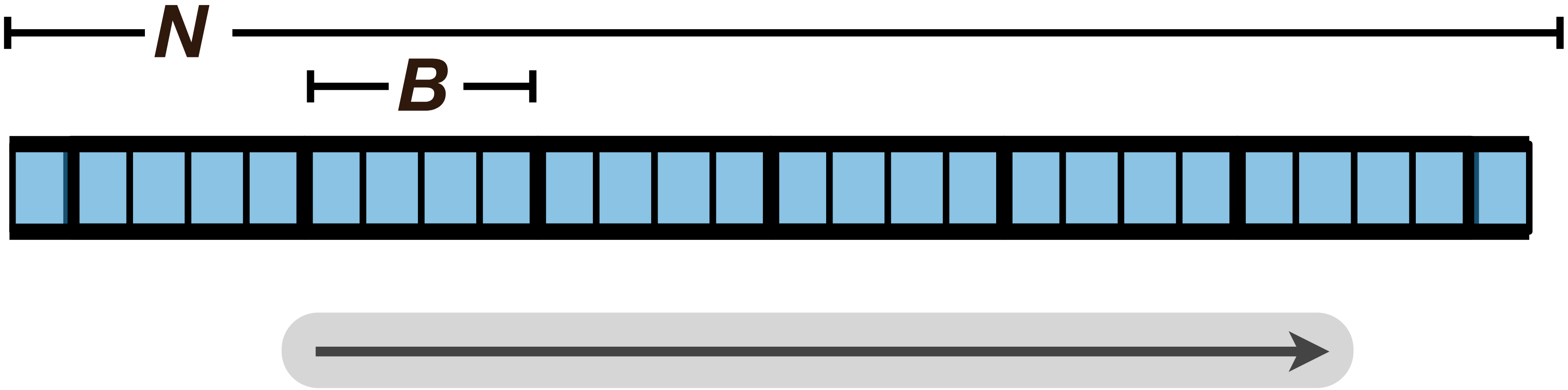
- Performance bounds are parameterized by block size ***B***, memory size ***M***, data size ***N***.



[Aggarwal+Vitter '88]

Example: Scanning an Array

Question: How many I/Os to scan an array of length *N*?



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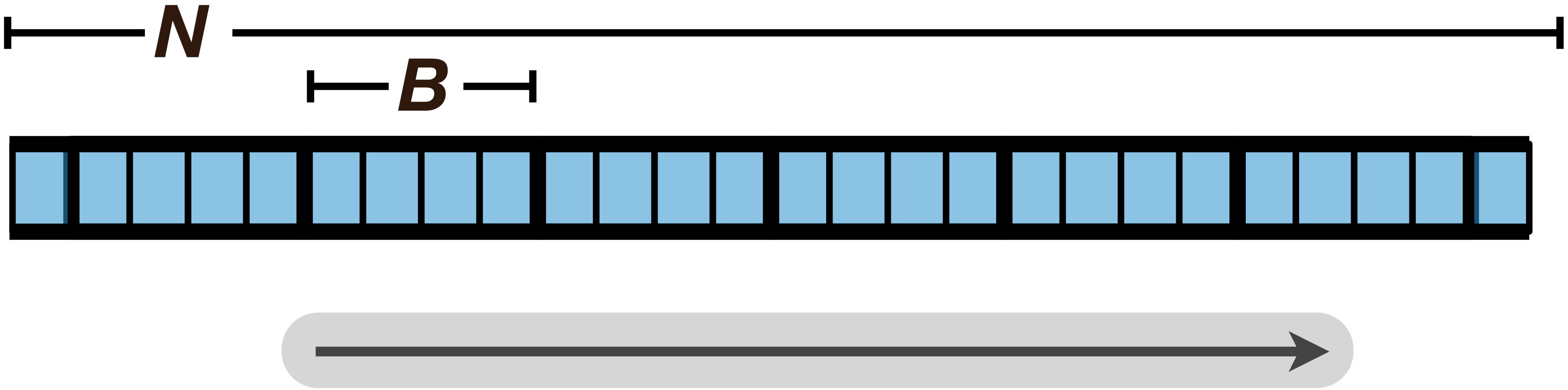

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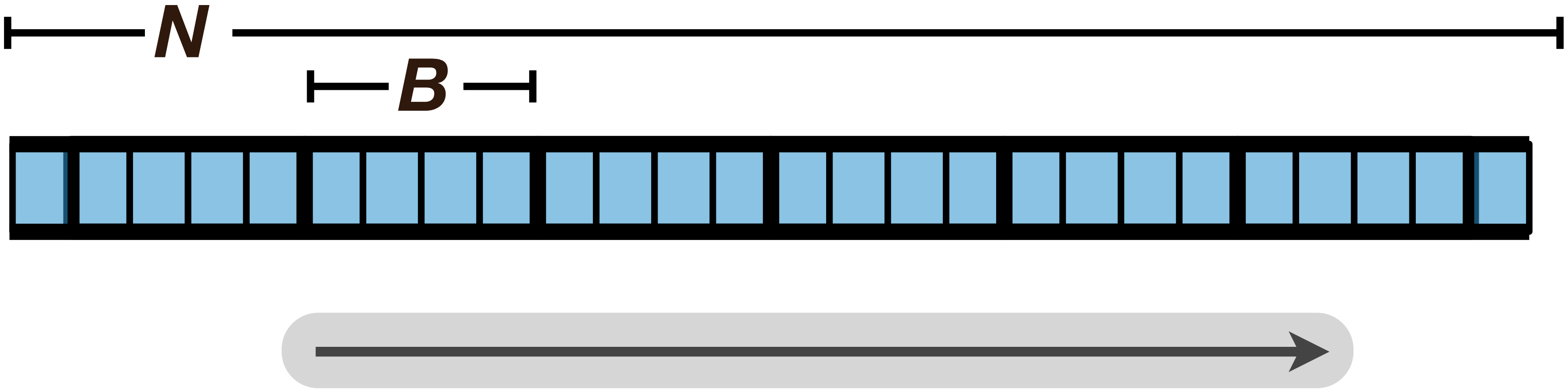
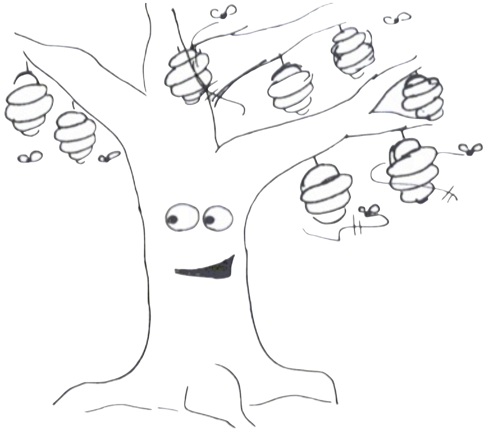
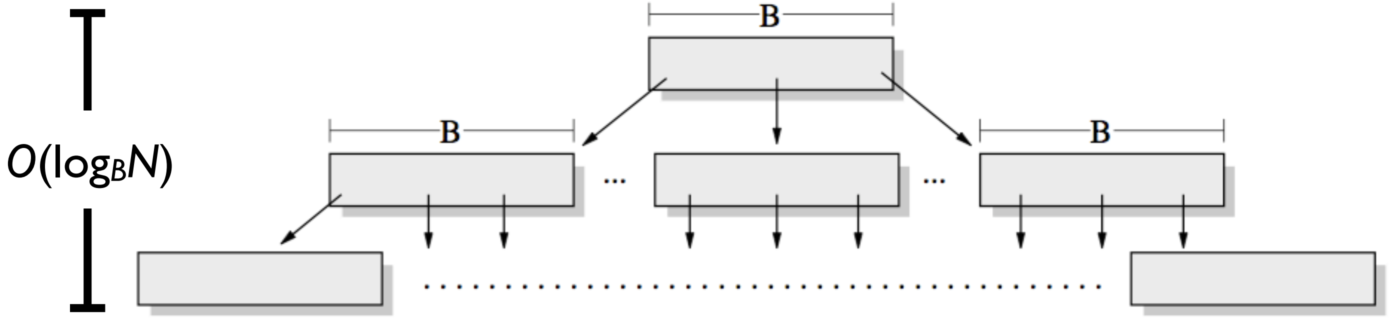


scan touches ≤ *N*/*B*+2 blocks

Example: Searching in a B-tree

Question: How many I/Os for a point query or insert into a B-tree with *N* elements?

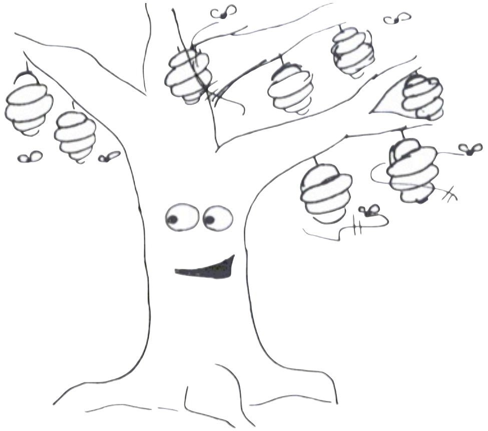


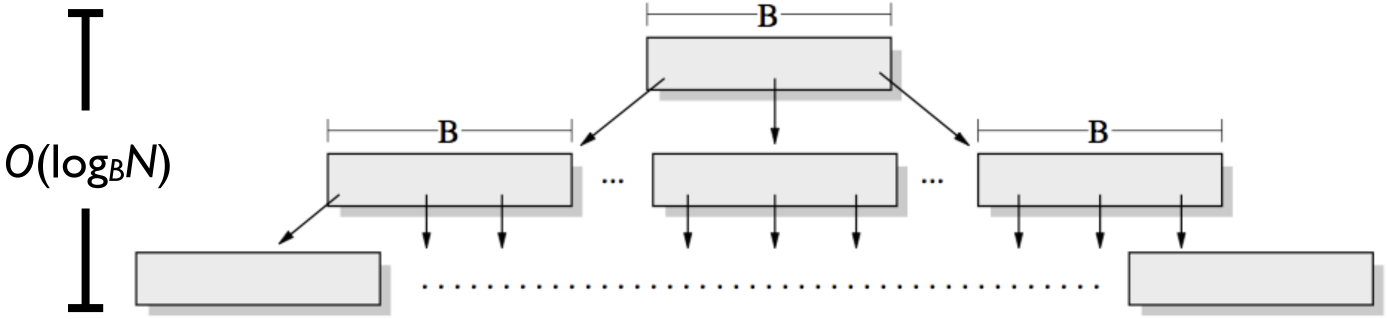


Example: Searching in a B-tree

Question: How many I/Os for a point query or insert into a B-tree with *N* elements?

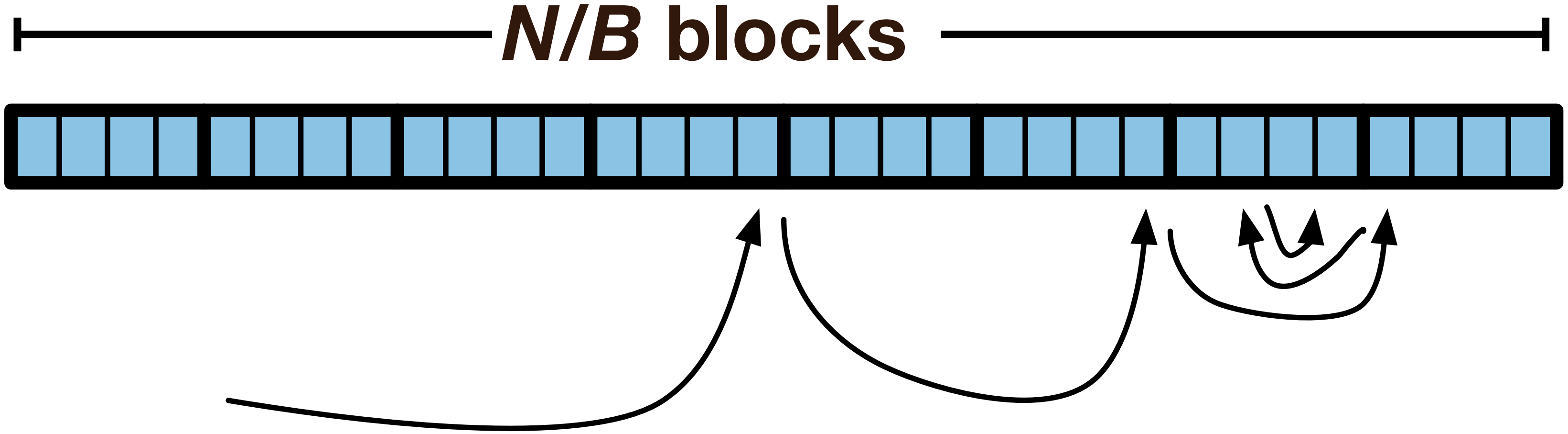
Answer: $O(\log_B N)$





Example: Searching in an Array

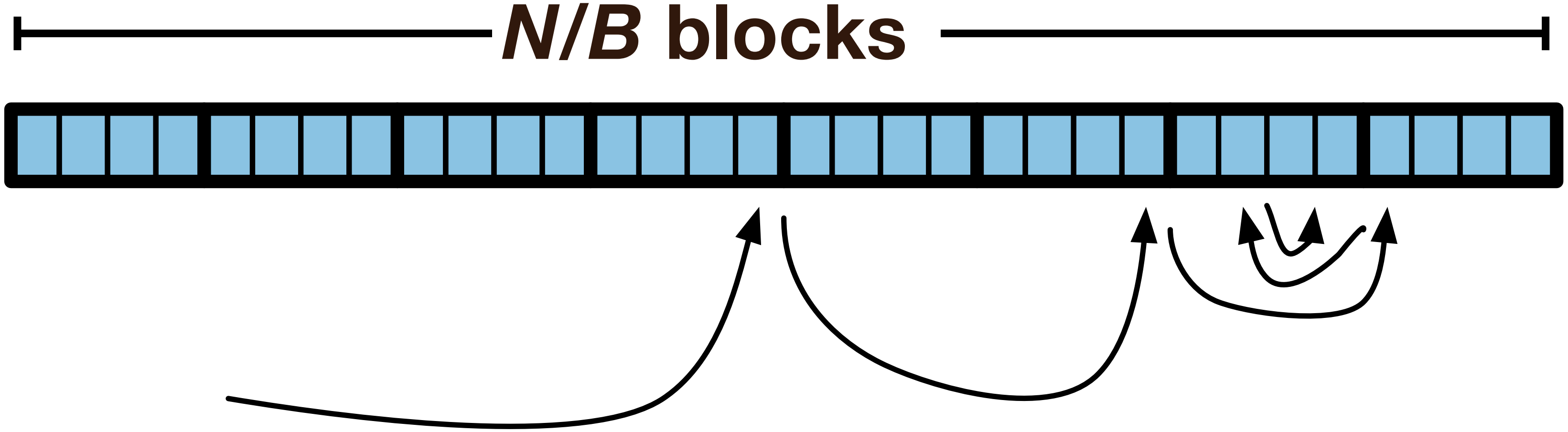
Question: How many I/Os to perform a binary search into an array of size *N*?



Example: Searching in an Array

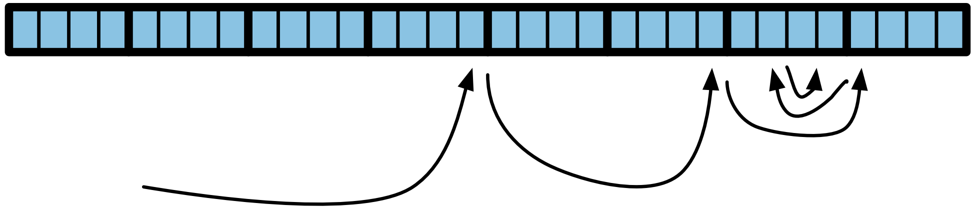
Question: How many I/Os to perform a binary search into an array of size *N*?

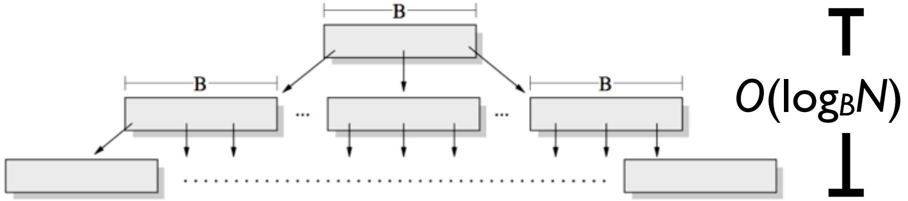
Answer: $$O\left(\log_2 \frac{N}{B}\right) \approx O(\log_2 N)$$



Example: Searching in an Array Versus B-tree

Moral: B-tree searching is a factor of $O(\log_2 B)$ faster than binary searching.





$$O(\log_2 N)$$

$$O(\log_B N) = O\left(\frac{\log_2 N}{\log_2 B}\right)$$

Example: I/O-Efficient Sorting

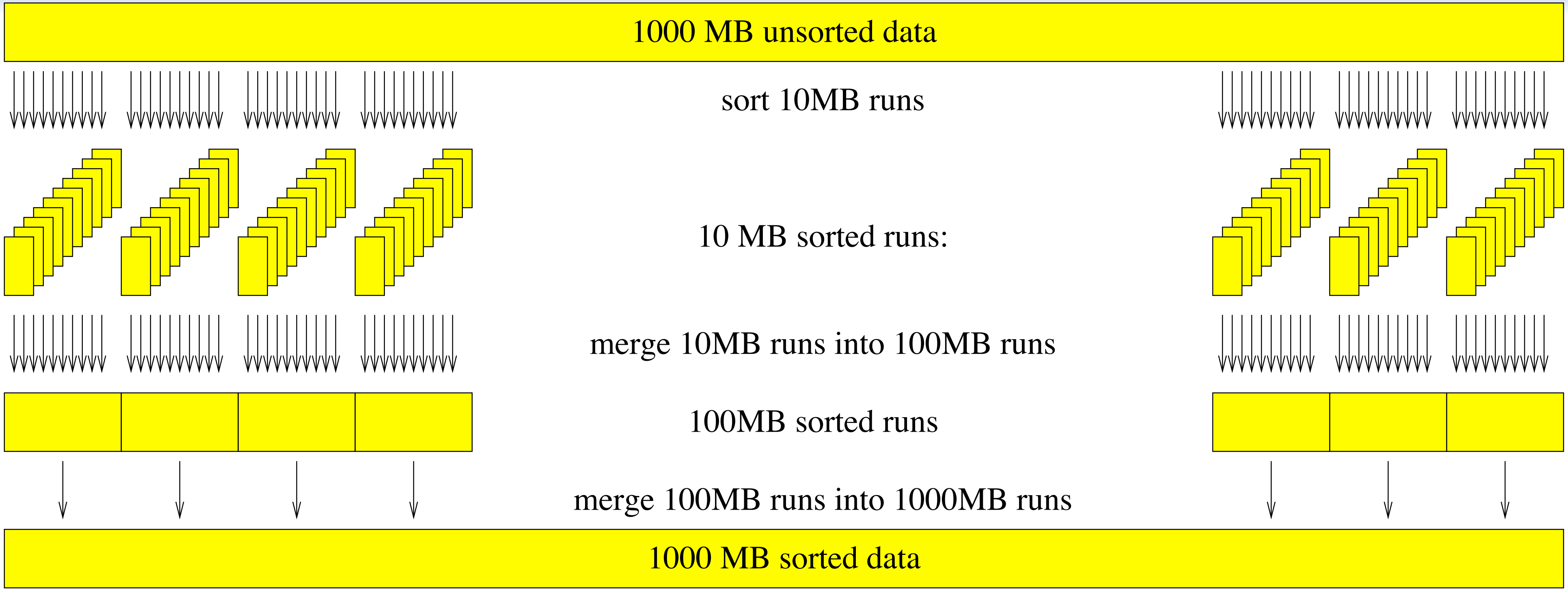
Imagine the following sorting problem:

- 1000 MB data
- 10 MB RAM
- 1 MB Disk Blocks

Here's a sorting algorithm

- Read in 10MB at a time, sort it, and write it out, producing 100 10MB "runs".
- Merge 10 10MB runs together to make a 100MB run. Repeat 10x.
- Merge 10 100MB runs together to make a 1000MB run.

I/O-Efficient Sorting in a Picture



1000 MB unsorted data

sort 10MB runs

10 MB sorted runs:

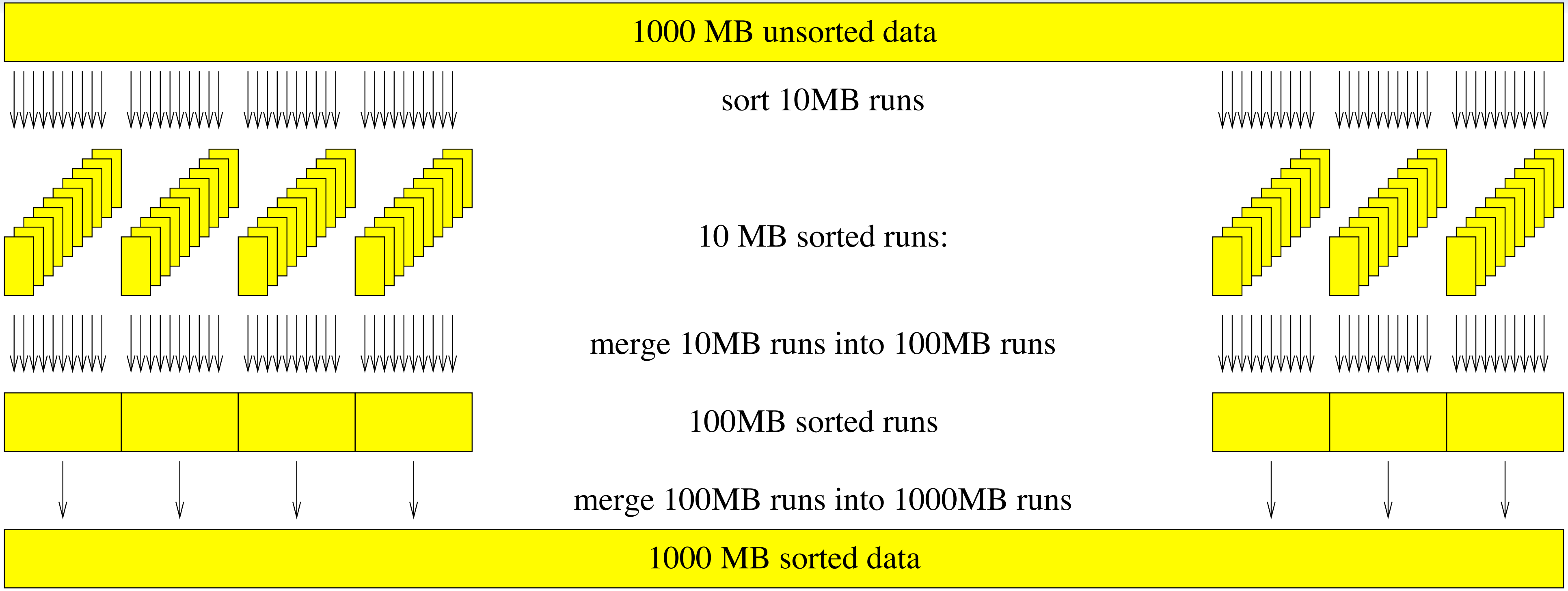
merge 10MB runs into 100MB runs

100MB sorted runs

merge 100MB runs into 1000MB runs

1000 MB sorted data

I/O-Efficient Sorting in a Picture



Why merge in two steps? We can only hold 10 blocks in main memory.

- 1000 MB data; 10 MB RAM;1 MB Disk Blocks

Merge Sort in General

Example

- Produce 10MB runs.
- Merge 10 10MB runs for 100MB.
- Merge 10 100MB runs for 1000MB.

becomes in general:

- Produce runs the size of main memory (size=M).
- Construct a merge tree with fanout M/B, with runs at the leaves.
- Repeatedly: pick a node that hasn't been merged.
  Merge the M/B children together to produce a bigger run.

Merge Sort Analysis

Question: How many I/Os to sort *N* elements?

- First run takes *N/B* I/Os.
- Each level of the merge tree takes *N/B* I/Os.
- How deep is the merge tree?

$$O\left(\underbrace{\frac{N}{B}}_{\text{Cost to scan data}}\ \underbrace{\log_{M/B}\frac{N}{B}}_{\text{\# of scans of data}}\right)$$

Merge Sort Analysis

Question: How many I/Os to sort *N* elements?

- First run takes *N*/*B* I/Os.
- Each level of the merge tree takes *N*/*B* I/Os.
- How deep is the merge tree?

$$O\left(\underbrace{\frac{N}{B}}_{\text{Cost to scan data}}\underbrace{\log_{M/B}\frac{N}{B}}_{\text{\# of scans of data}}\right)$$

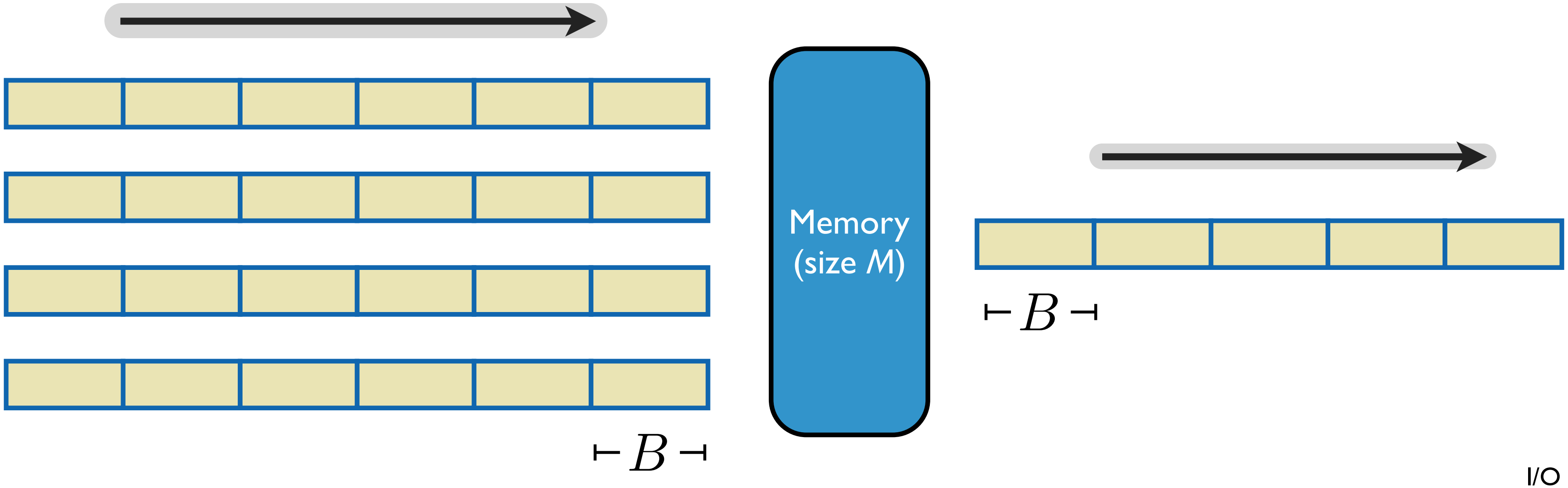
This bound is the best possible.

Merge Sort as Divide-and-Conquer

To sort an array of *N* objects

- If *N* fits in main memory, then just sort elements.
- Otherwise,
  -- divide the array into *M*/*B* pieces;
  -- sort each piece (recursively); and
  -- merge the *M*/*B* pieces.

This algorithm has the same I/O complexity.



Analysis of divide-and-conquer

Recurrence relation:

$$T(N) = \overset{\text{\# of pieces}}{\frac{M}{B}} \cdot \overset{\text{cost to sort each piece recursively}}{T\left(\frac{N}{M/B}\right)} + \overset{\text{cost to merge}}{\frac{N}{B}}$$

$$T(N) = \frac{N}{B} \quad \text{when } N < M \qquad \text{cost to sort something that fits in memory}$$

Solution:

$$O\left(\underbrace{\frac{N}{B}}_{\text{Cost to scan data}} \underbrace{\log_{M/B} \frac{N}{B}}_{\text{\# of scans of data}}\right)$$

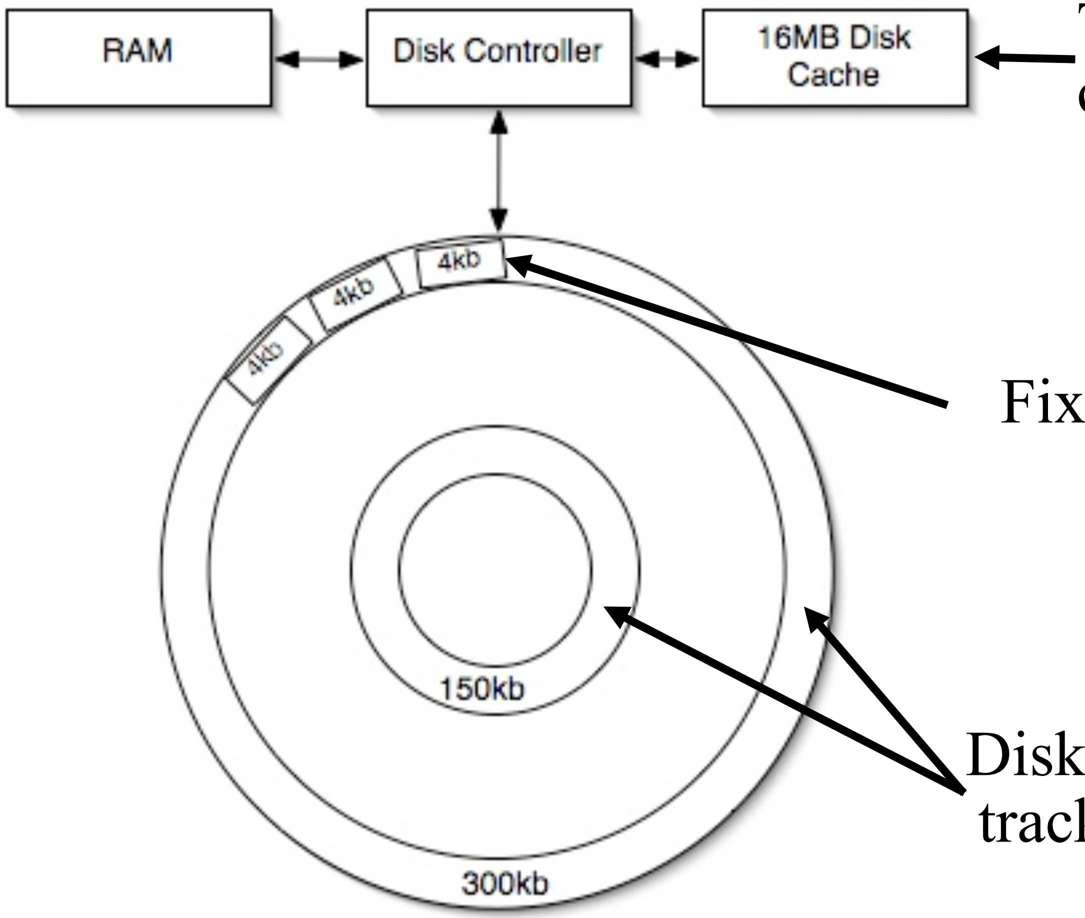
Ignore CPU costs

The Disk Access Machine (DAM) model

- ignores CPU costs and
- assumes that all block accesses have the same cost.

Is that a good performance model?

The DAM Model is a Simplification



Tracks get prefetched into the disk cache, which holds ~100 tracks.

Fixed-size blocks are fetched.

Disks are organized into tracks of different sizes

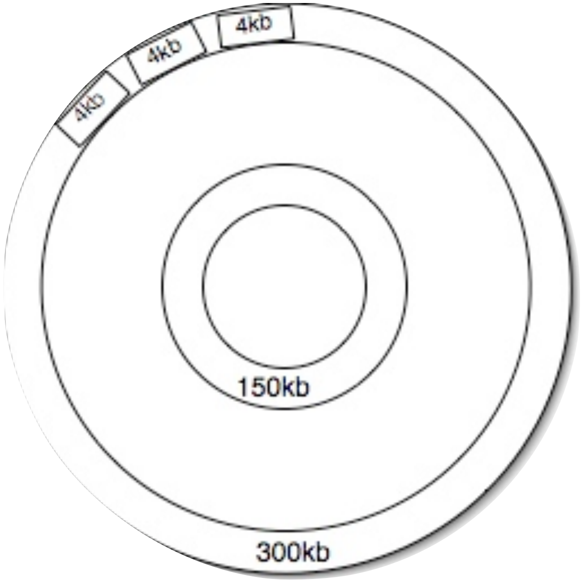
The DAM Model is a Simplification

2kB or 4kB is too small for the model.

- B-tree nodes in Berkeley DB & InnoDB have this size.
- Issue: sequential block accesses run 10x faster than random block accesses, which doesn't fit the model.

There is no single best block size.

- The best node size for a B-tree depends on the operation (insert/delete/point query).

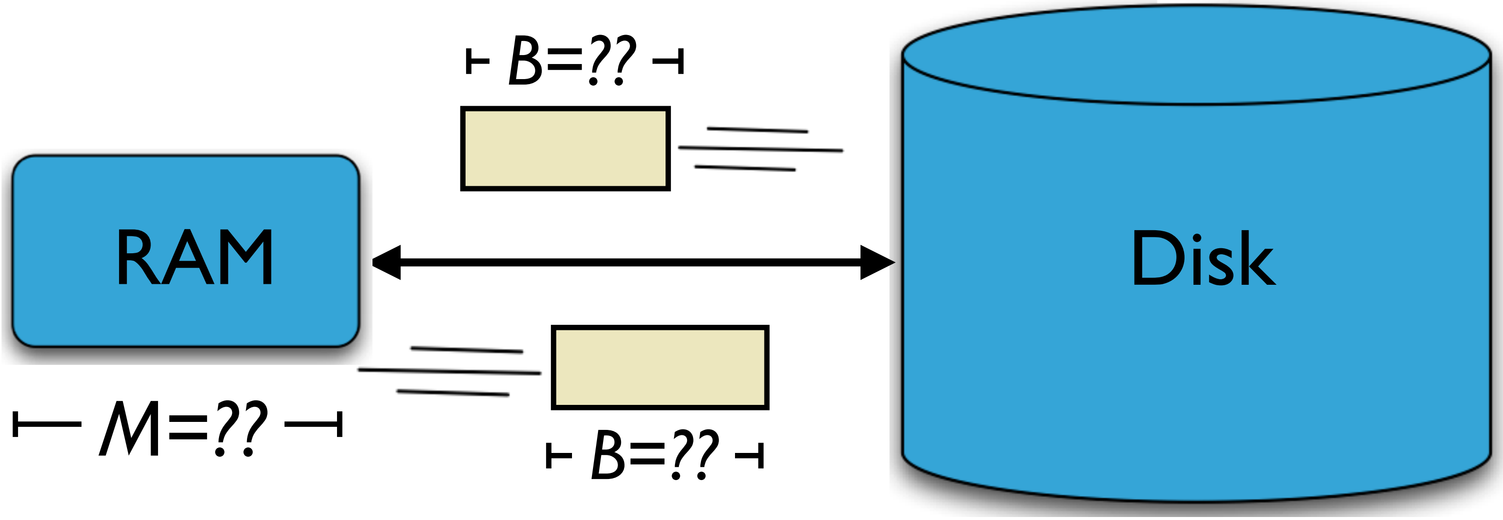


Cache-Oblivious Analysis

Cache-oblivious analysis:

- Parameters B, M are unknown to the algorithm or coder.
- Performance bounds are parameterized by block size B, memory size M, data size N.

Goal (as before): Minimize # of block transfer

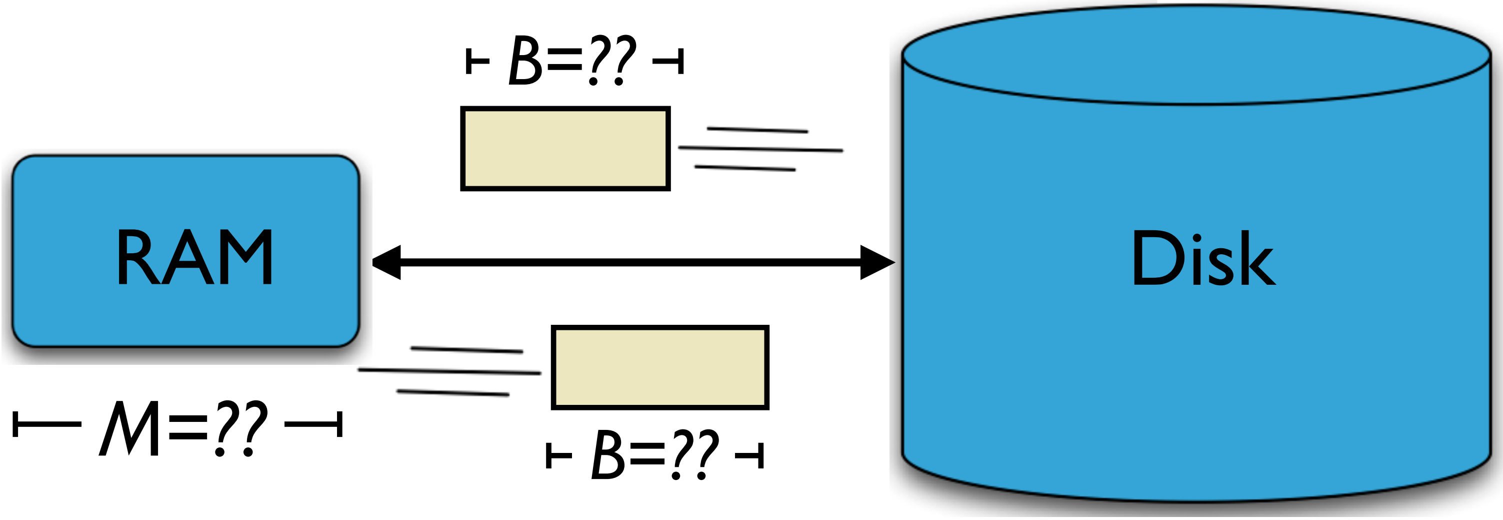


[Frigo, Leiserson, Prokop, Ramachandran ’99]

Cache-Oblivious Model

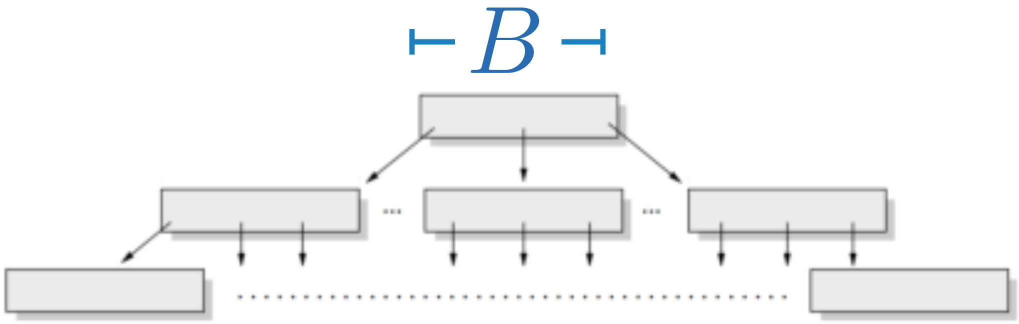
- Cache-oblivious algorithms work for all *B* and *M*...
- ... and all levels of a multi-level hierarchy.

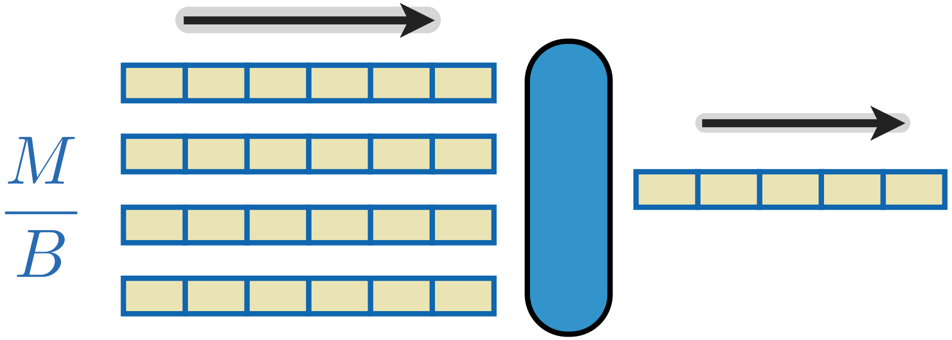
It's better to optimize approximately for all B, M than to pick the best B and M.



[Frigo, Leiserson, Prokop, Ramachandran '99]

B-trees, k-way Merge Sort Aren’t Cache-Oblivious





Fan-out is a function of *B*.

Fan-in is a function of *M* and *B*.

Surprisingly, there are cache-oblivious B-trees and cache-oblivious sorting algorithms.

[Frigo, Leiserson, Prokop, Ramachandran ’99] [Bender, Demaine, Farach-Colton ’00] [Bender, Duan, Iacono, Wu ’02] [Brodal, Fagerberg, Jacob ’02] [Brodal, Fagerberg, Vinther ’04]

Time for 1000 Random Searches

[Bender, Farach-Colton, Kuszmaul '06]

B	Small	Big
4K	17.3ms	22.4ms
16K	13.9ms	22.1ms
32K	11.9ms	17.4ms
64K	12.9ms	17.6ms
128K	13.2ms	16.5ms
256K	18.5ms	14.4ms
512K		16.7ms

	Small	Big
CO B-tree	12.3ms	13.8ms

There's no best block size.

The optimal block size for inserts is very different.

Summary

Algorithmic models of the memory hierarchy explain how DB data structures scale.

- There's a long history of models of the memory hierarchy. Many are beautiful. Most haven't seen practical use.

DAM and cache-oblivious analysis are powerful

- Parameterized by block size B and memory size M.
- In the CO model, B and M are unknown to the coder.

Data Structures and Algorithms for Big Data

Module 2: Write-Optimized Data Structures

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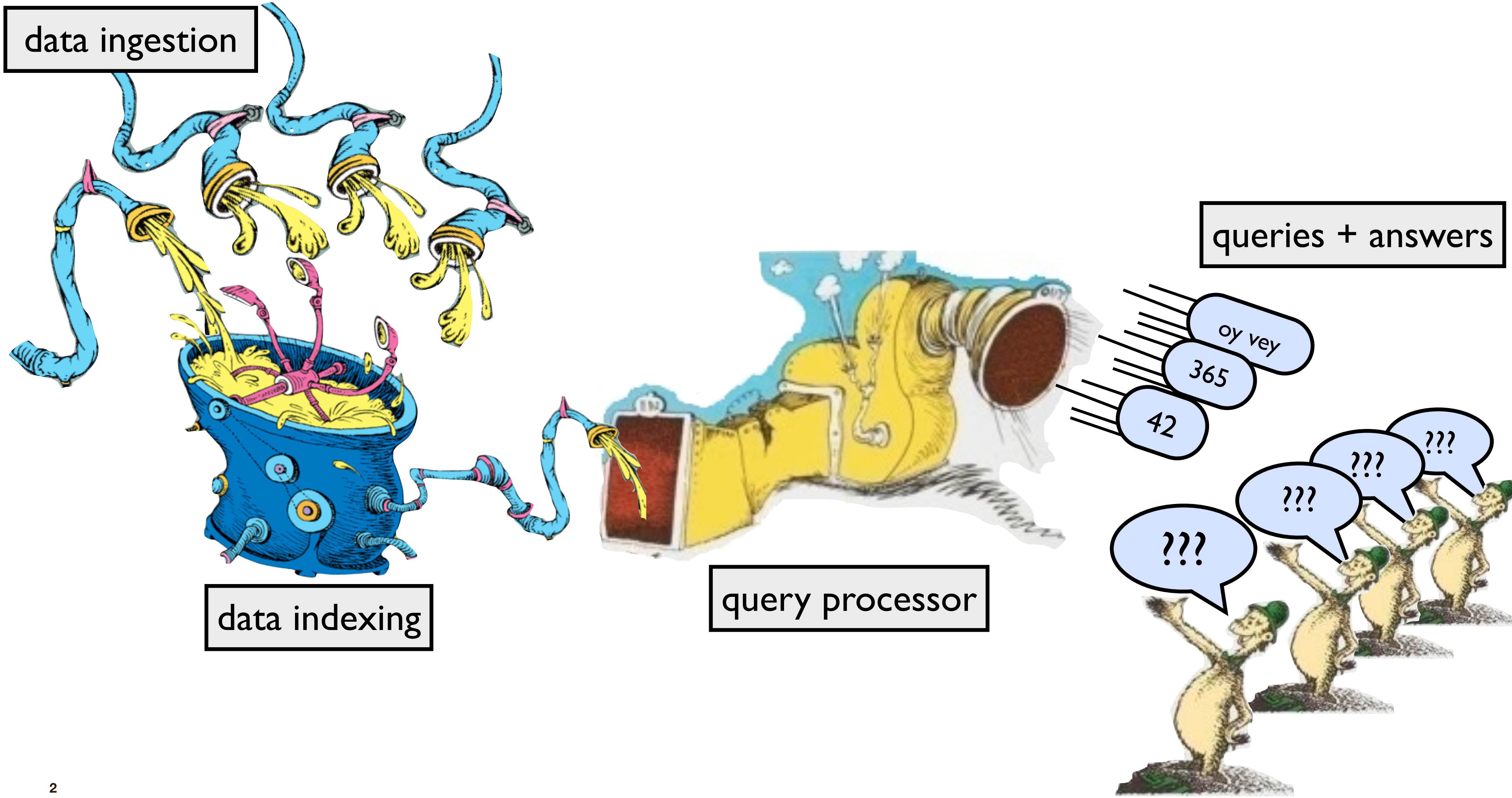

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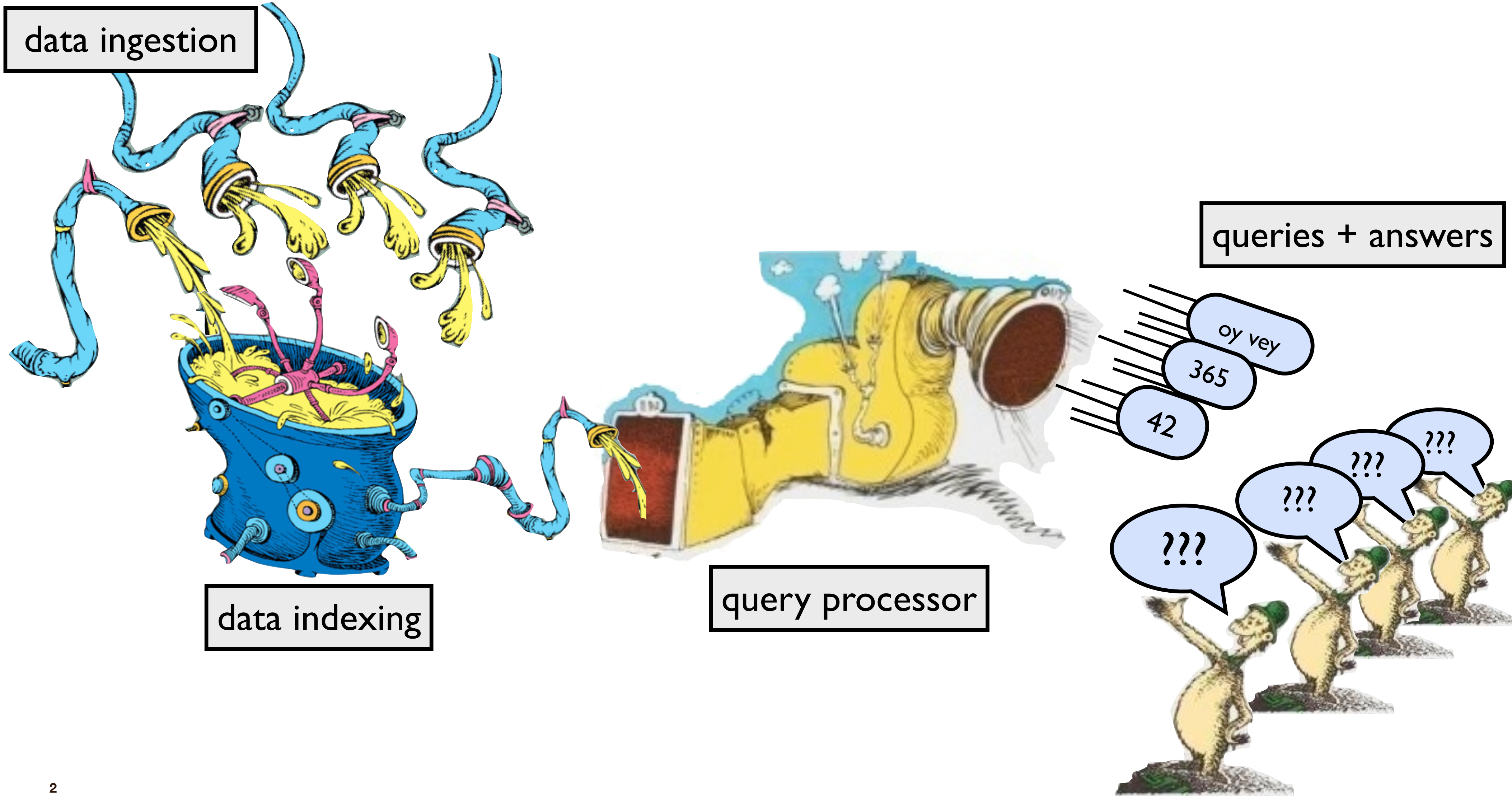
For on-disk data, one sees funny tradeoffs in the speeds of data ingestion, query speed, and freshness of data.



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Funny tradeoff in ingestion, querying, freshness

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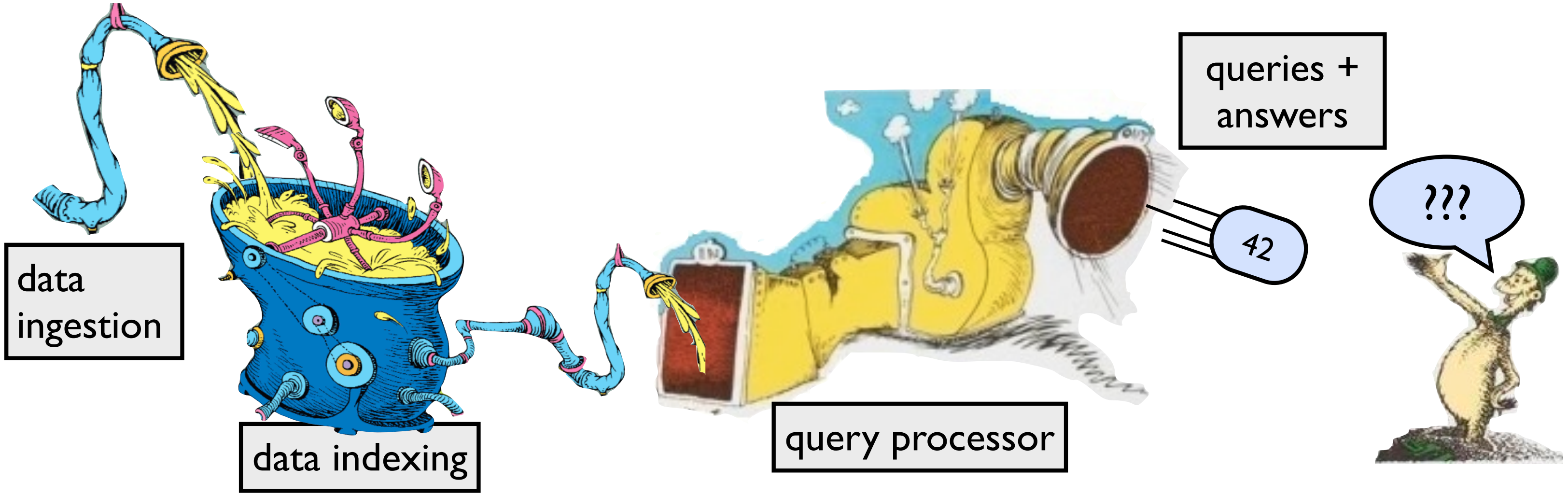

Funny tradeoff in ingestion, querying, freshness

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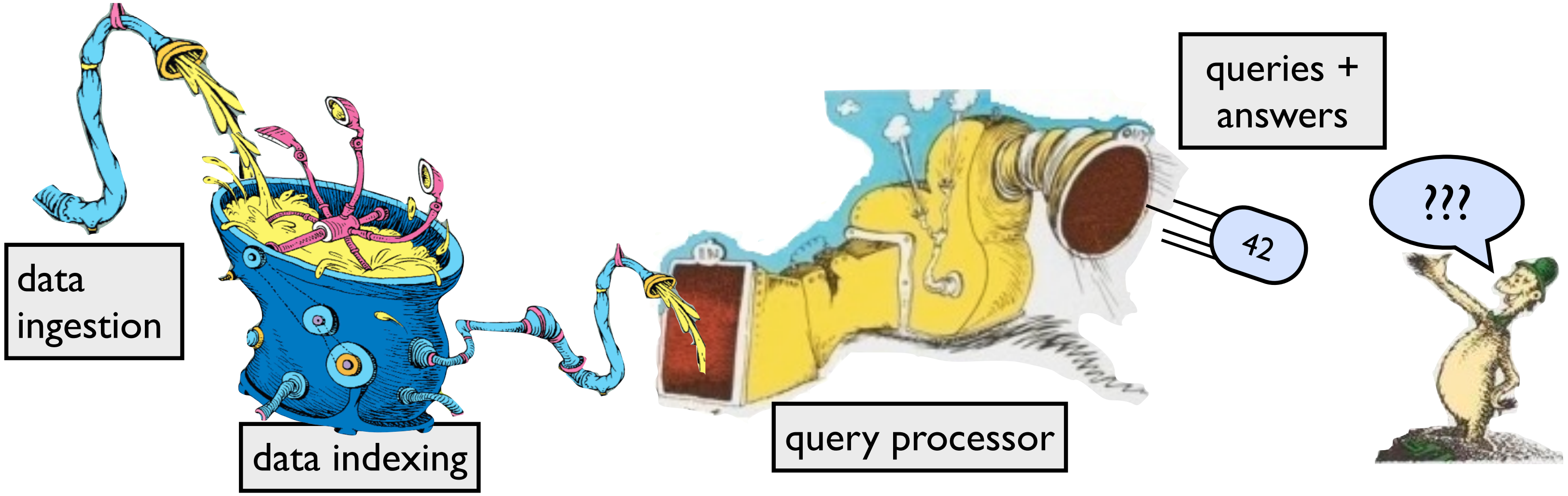

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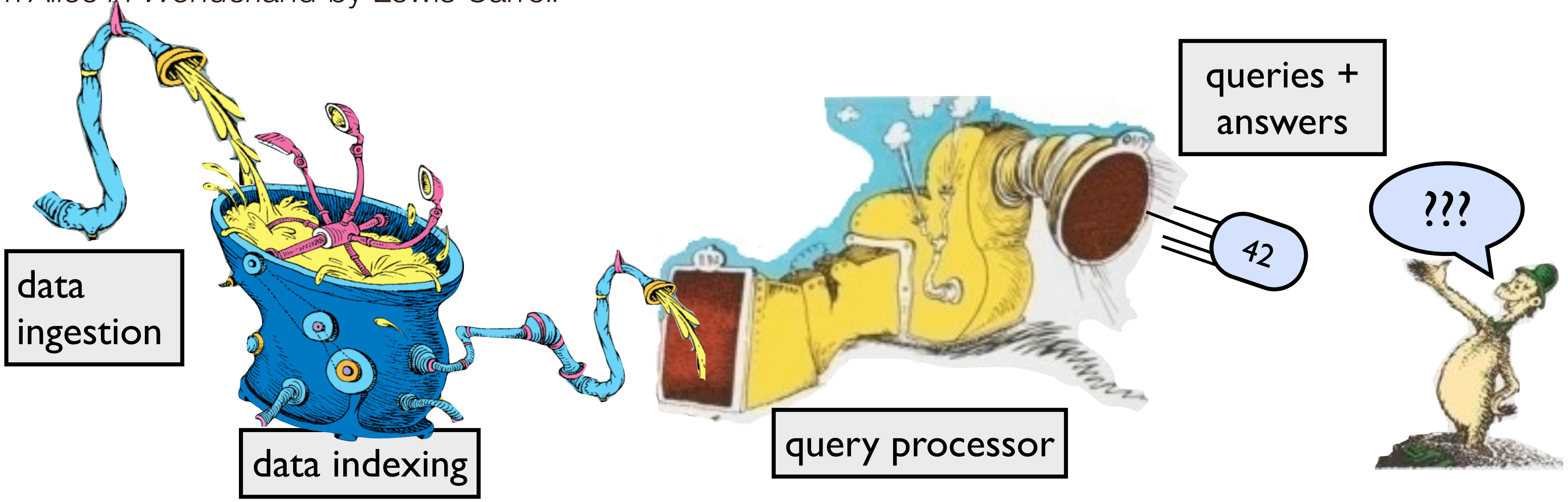
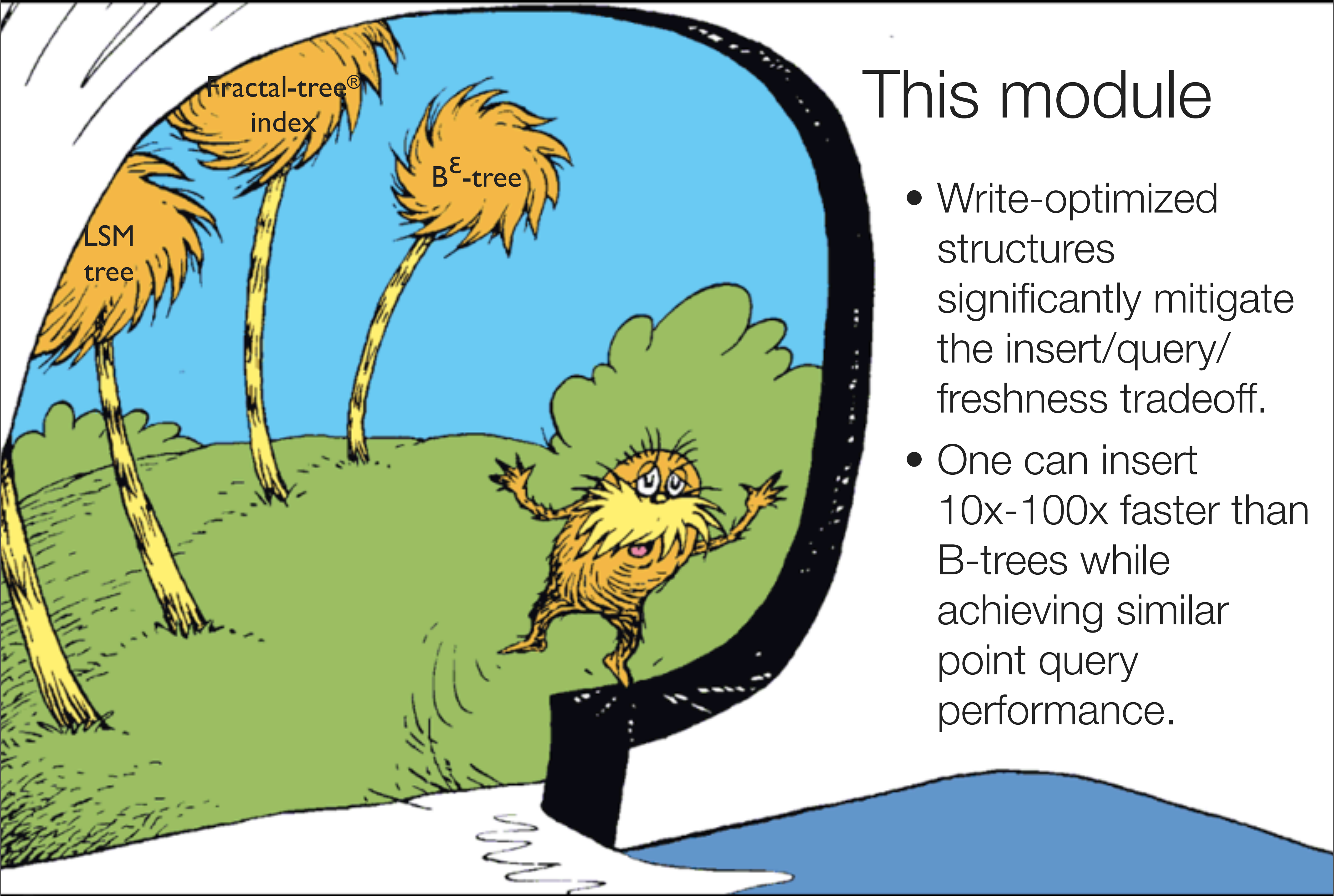
  But that wasn't the last of their troubles, to tell–
  Their insertions, like treacle, ran thick."
  - Not from *Alice in Wonderland* by Lewis Carroll



This module



- Write-optimized structures significantly mitigate the insert/query/freshness tradeoff.
- One can insert 10x-100x faster than B-trees while achieving similar point query performance.

An algorithmic performance model

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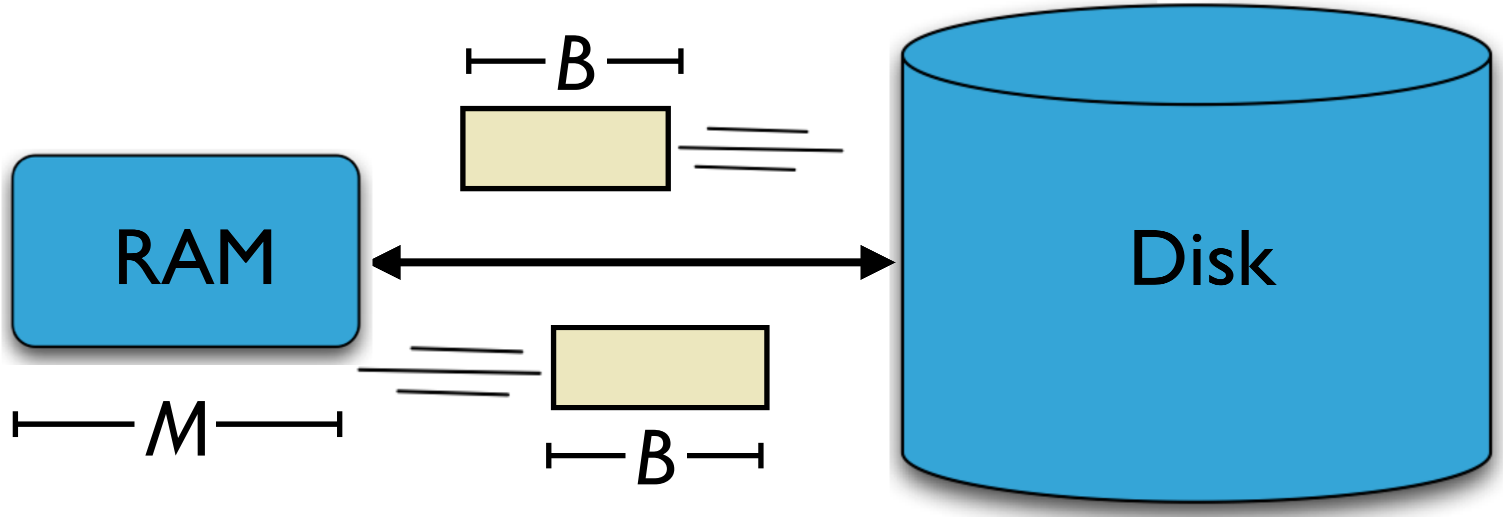
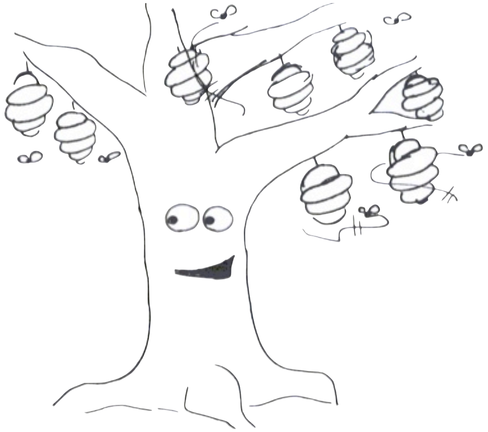
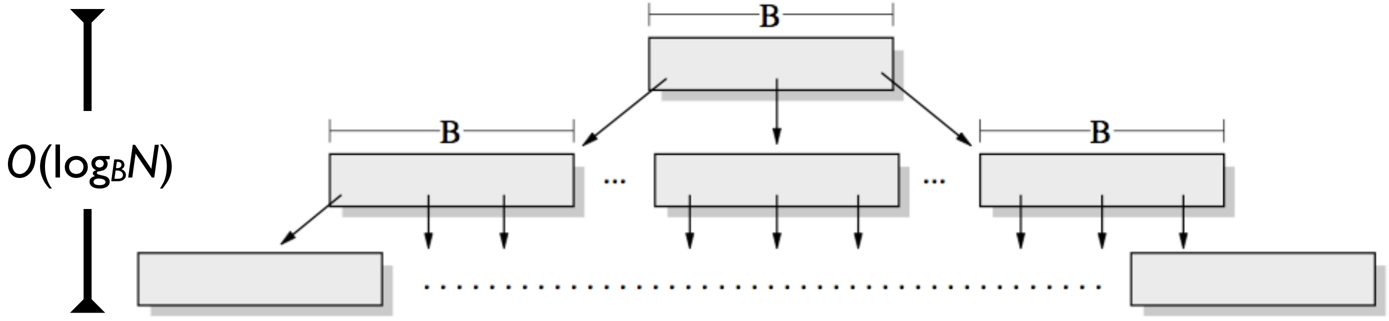


[Aggarwal+Vitter '88]

An algorithmic performance model

B-tree point queries: O($\log_B N$) I/Os.





Write-optimized data structures performance

Data structures: [O'Neil,Cheng, Gawlick, O'Neil 96], [Buchsbaum, Goldwasser, Venkatasubramanian, Westbrook 00], [Argel 03], [Graefe 03], [Brodal, Fagerberg 03], [Bender, Farach,Fineman,Fogel, Kuszmaul, Nelson'07], [Brodal, Demaine, Fineman, Iacono, Langerman, Munro 10], [Spillane, Shetty, Zadok, Archak, Dixit 11].
Systems: BigTable, Cassandra, H-Base, LevelDB, TokuDB.

	B-tree	Some write-optimized structures
Insert/delete	$O(\log_B N)=O\left(\frac{\log N}{\log B}\right)$	$O\left(\frac{\log N}{B}\right)$

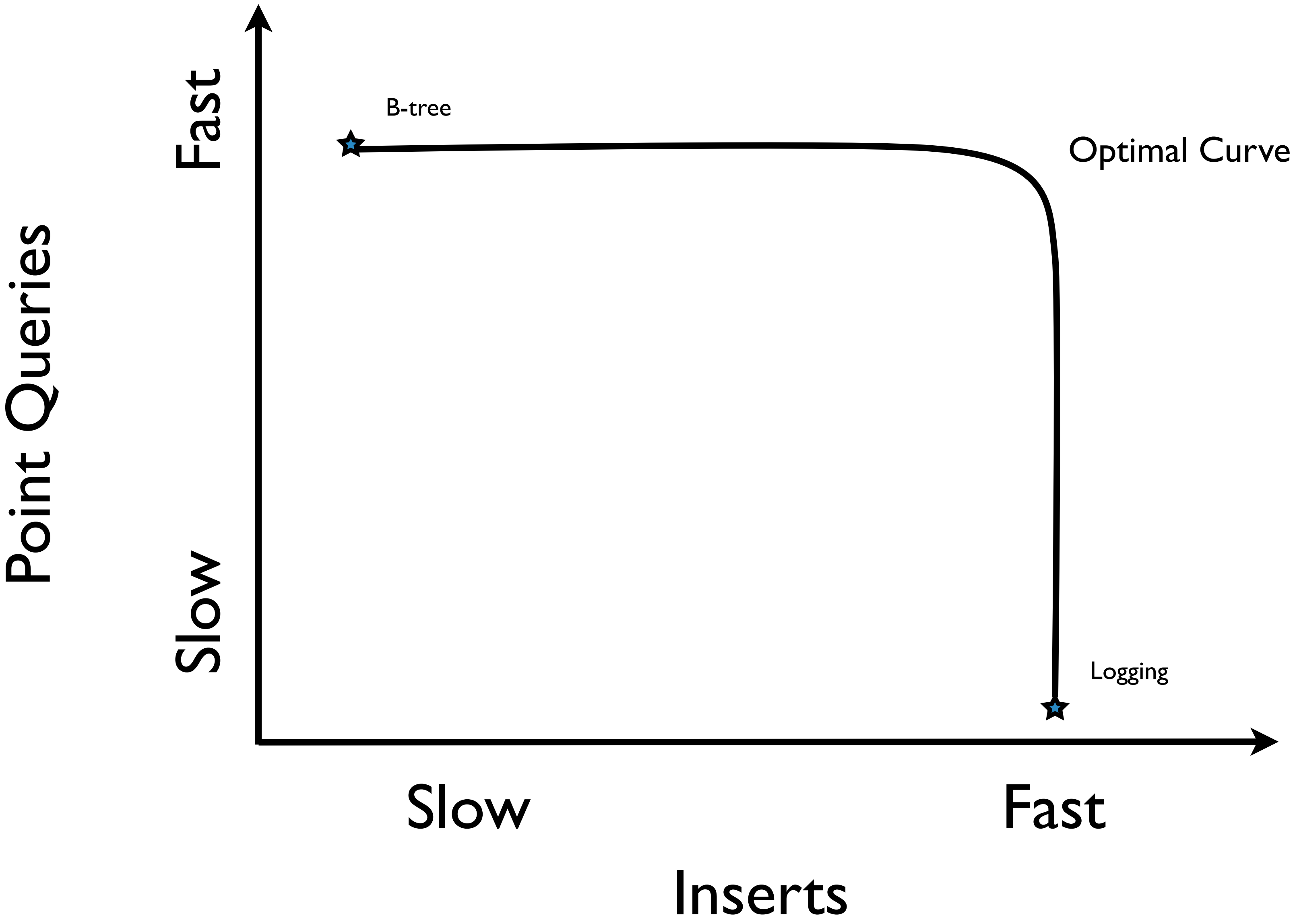
- If B=1024, then insert speedup is $B/\log B \approx 100$.
- Hardware trends mean bigger B, bigger speedup.
- Less than 1 I/O per insert.

Optimal Search-Insert Tradeoff [Brodal, Fagerberg 03]

	insert	**point query**
Optimal tradeoff (function of ε=0...1)	$O\left(\frac{\log_{1+B^\varepsilon} N}{B^{1-\varepsilon}}\right)$	$O\left(\log_{1+B^\varepsilon} N\right)$
B-tree (ε=1)	$O\left(\log_B N\right)$	$O\left(\log_B N\right)$
ε=1/2	$O\left(\frac{\log_B N}{\sqrt{B}}\right)$	$O\left(\log_B N\right)$
ε=0	$O\left(\frac{\log N}{B}\right)$	$O\left(\log N\right)$

10x-100x faster inserts

Illustration of Optimal Tradeoff [Brodal, Fagerberg 03]



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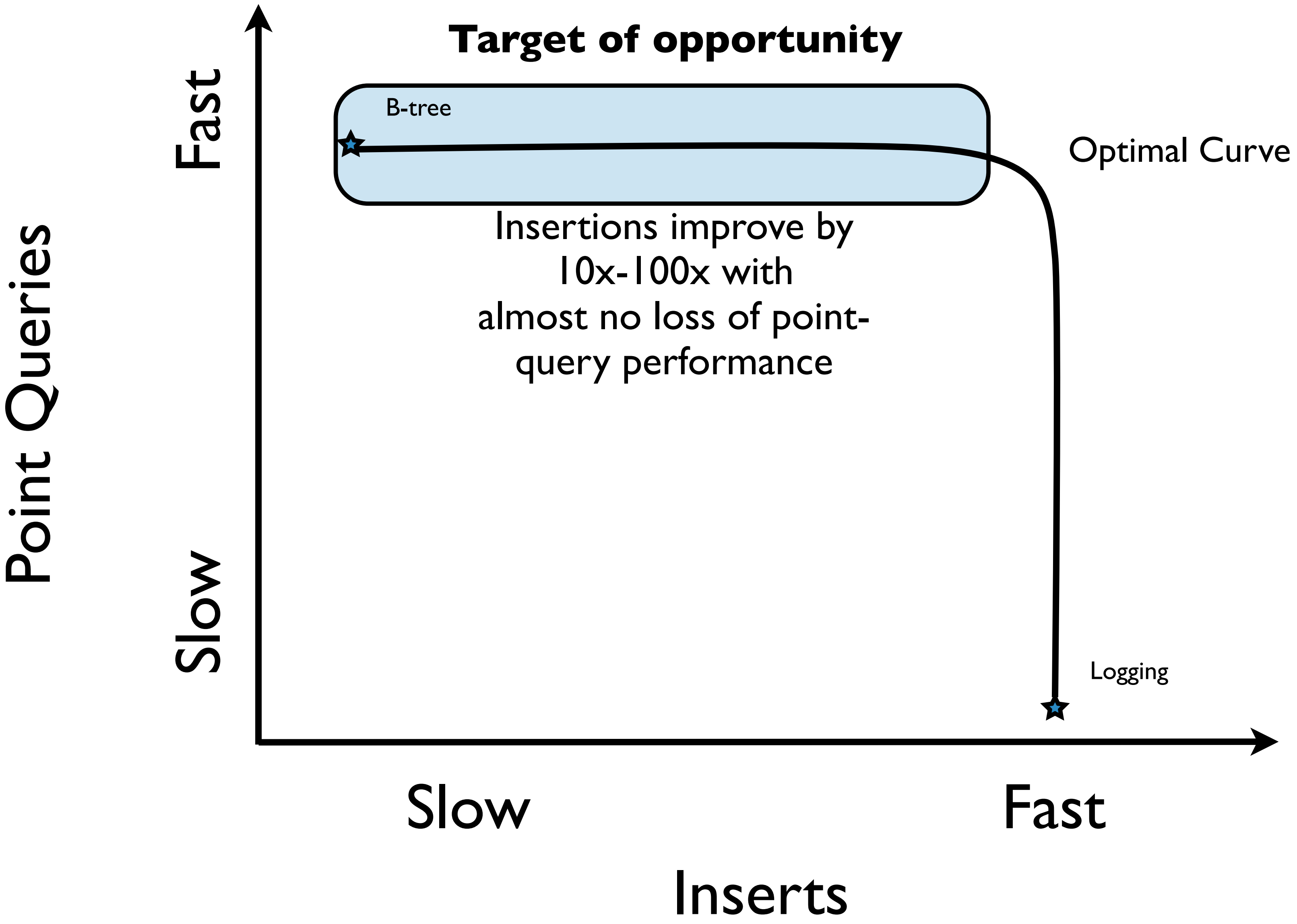

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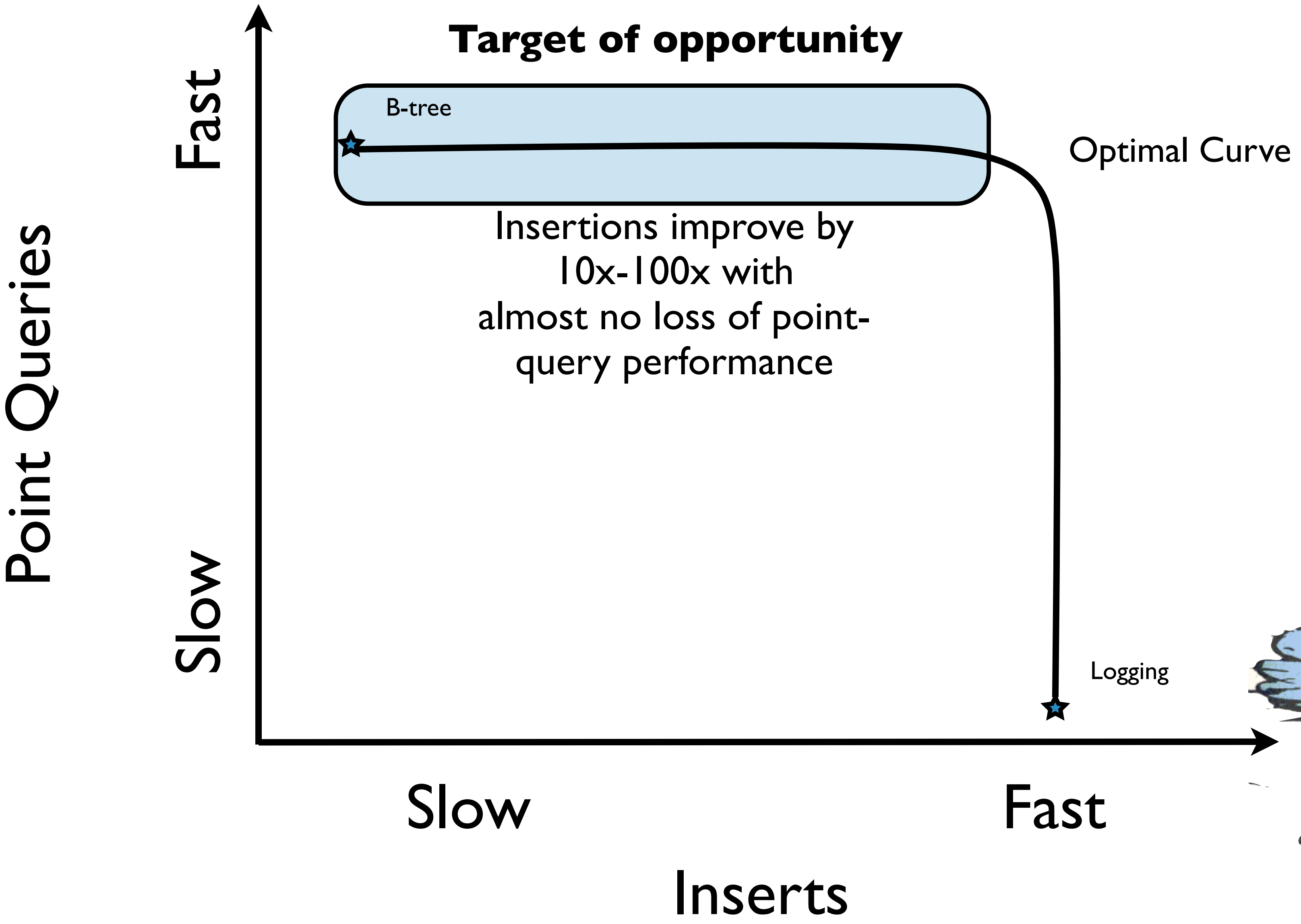


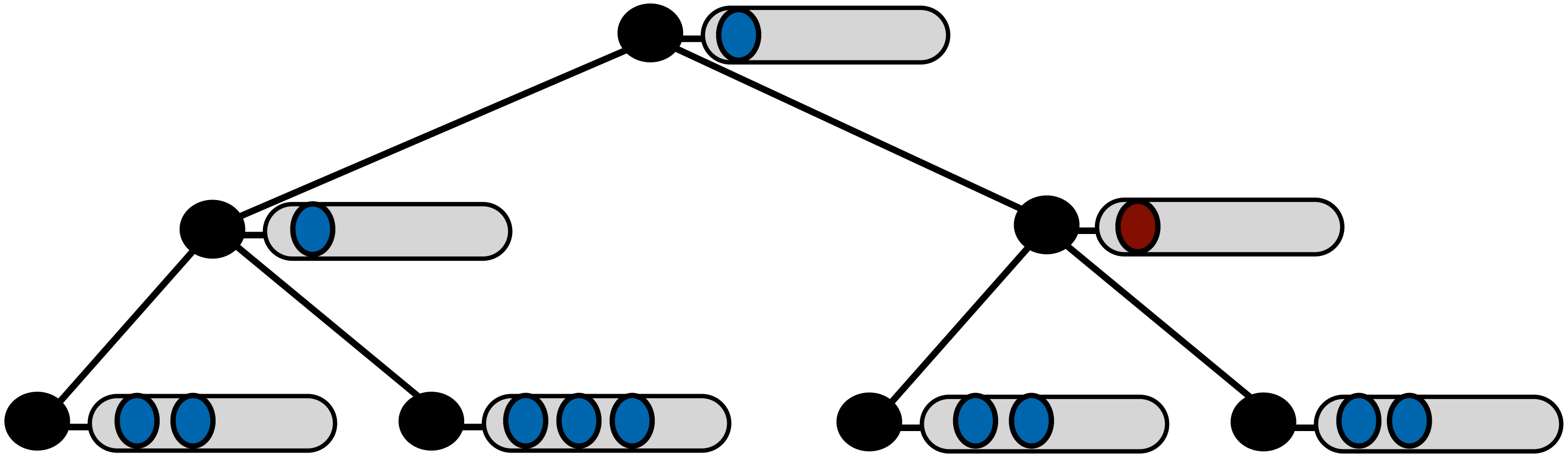
One way to Build Write-Optimized Structures

(Other approaches later)

A simple write-optimized structure

O(log *N*) queries and O((log *N*)/*B*) inserts:

- A balanced binary tree with buffers of size *B*



Inserts + deletes:

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- When a buffer fills up, flush.

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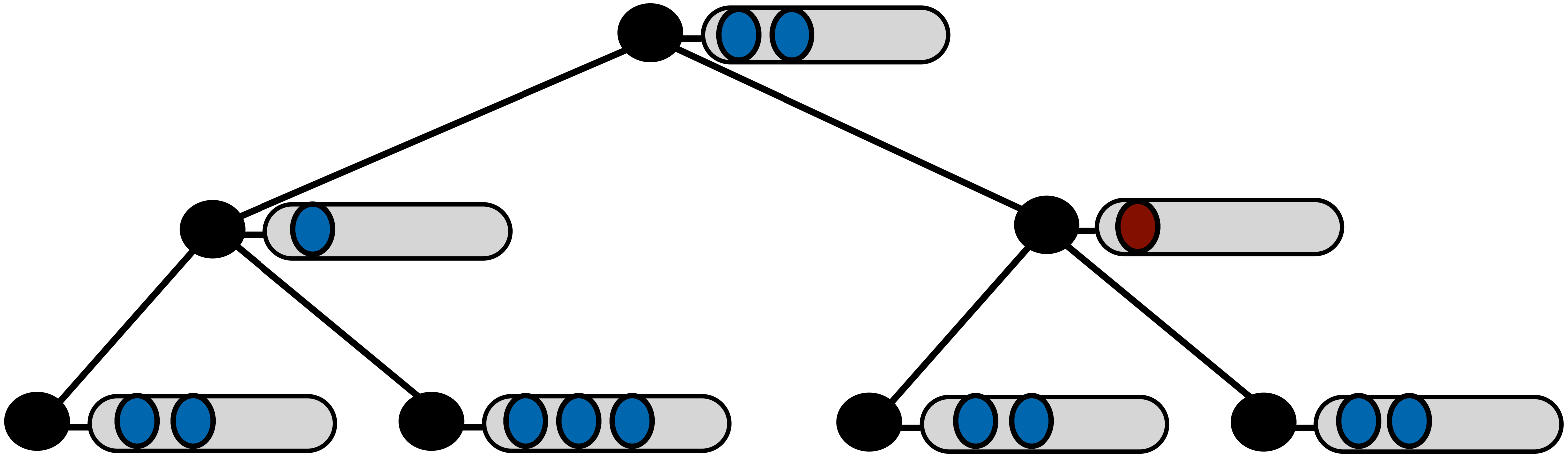

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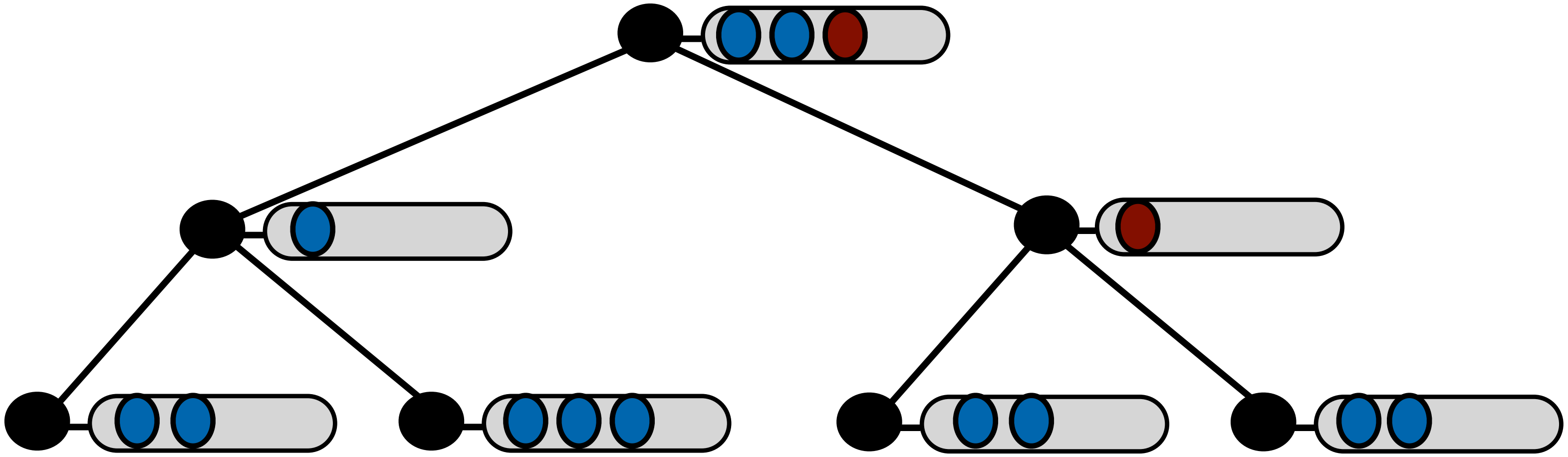

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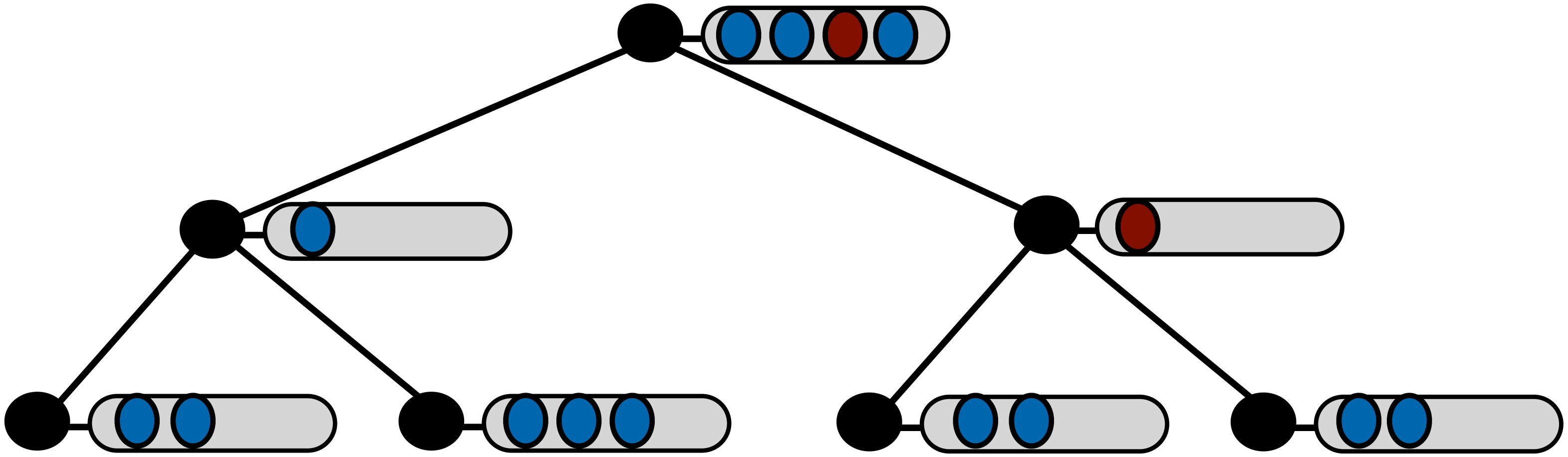

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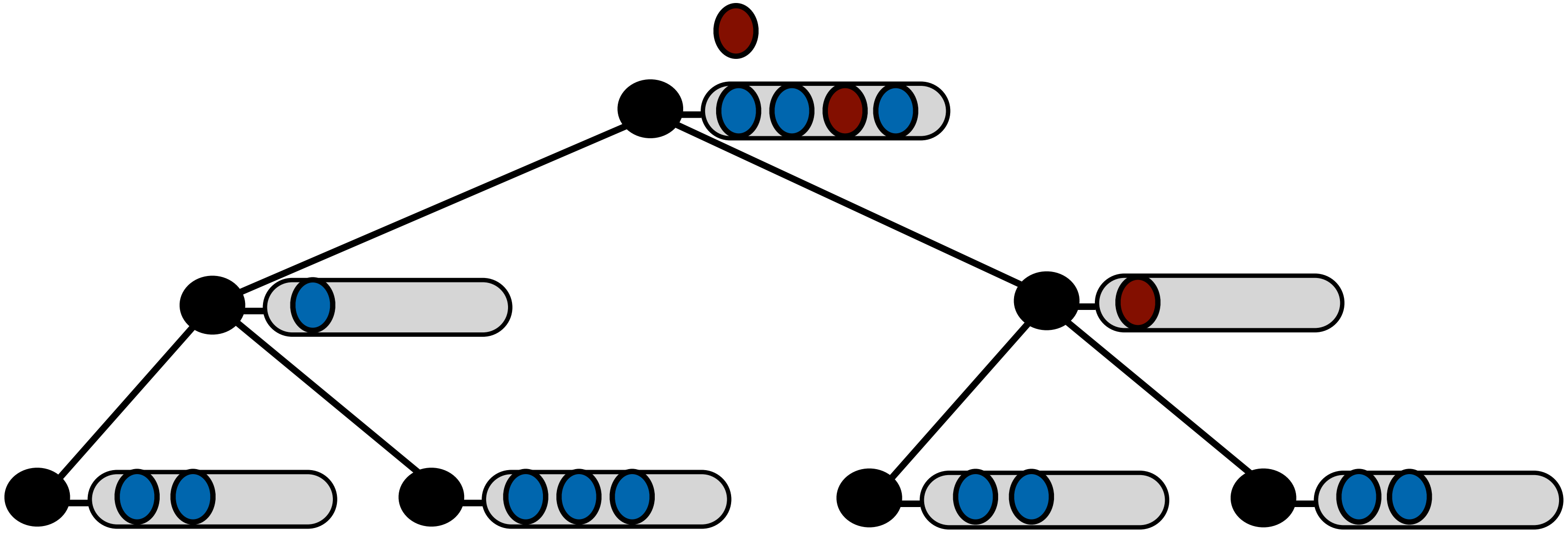

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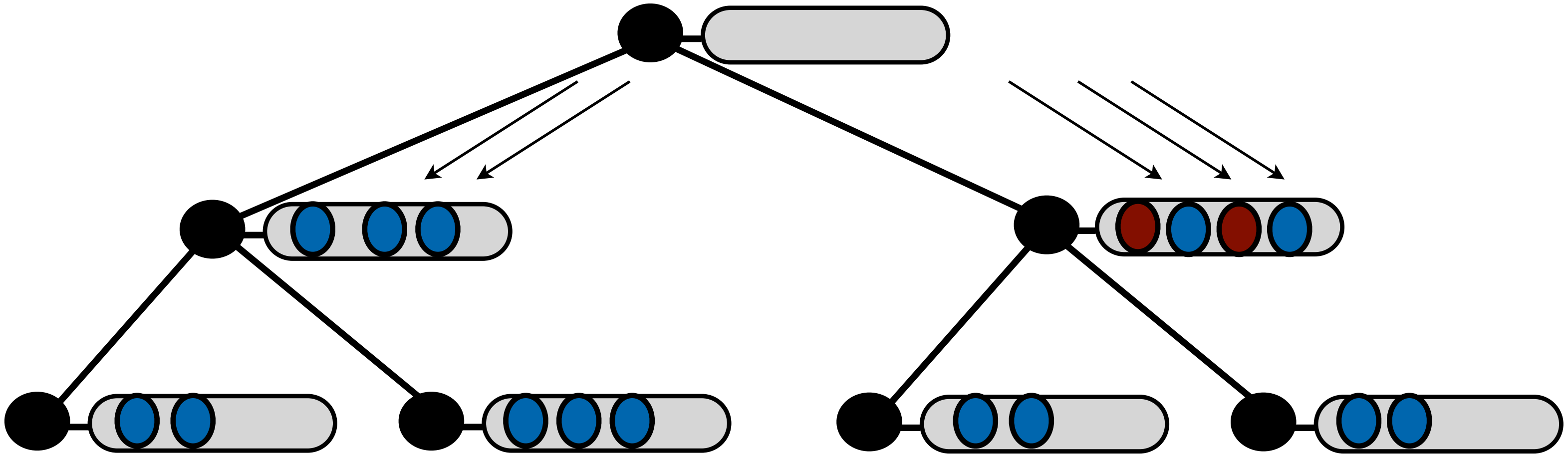


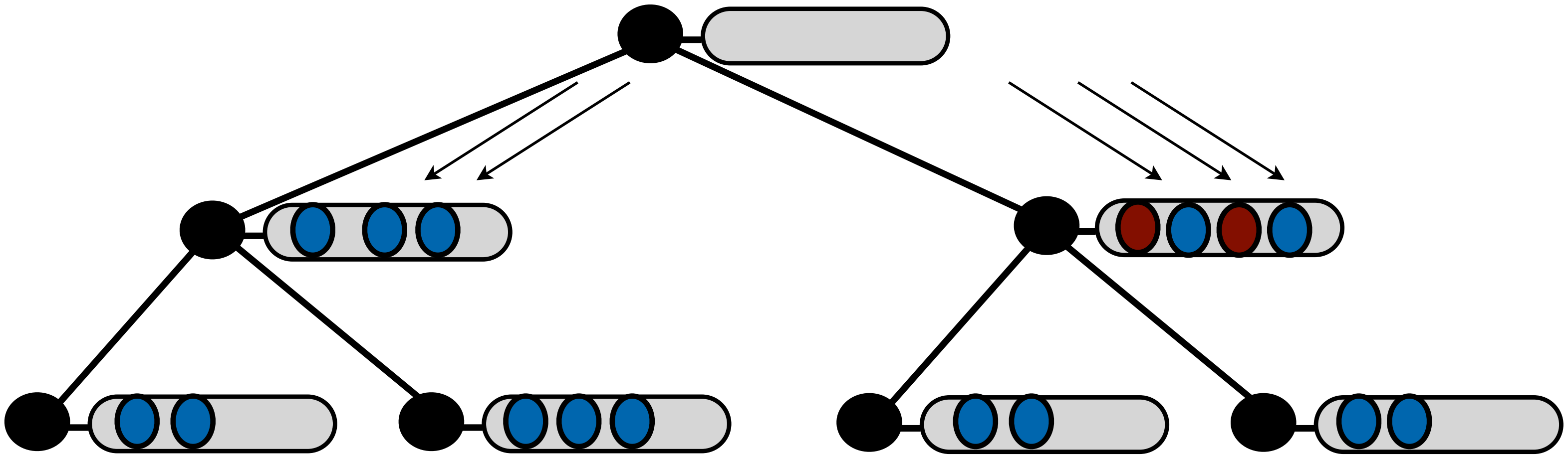
Inserts + deletes:

- Send insert/delete messages down from the root and store them in buffers.
- When a buffer fills up, flush.

Analysis of writes

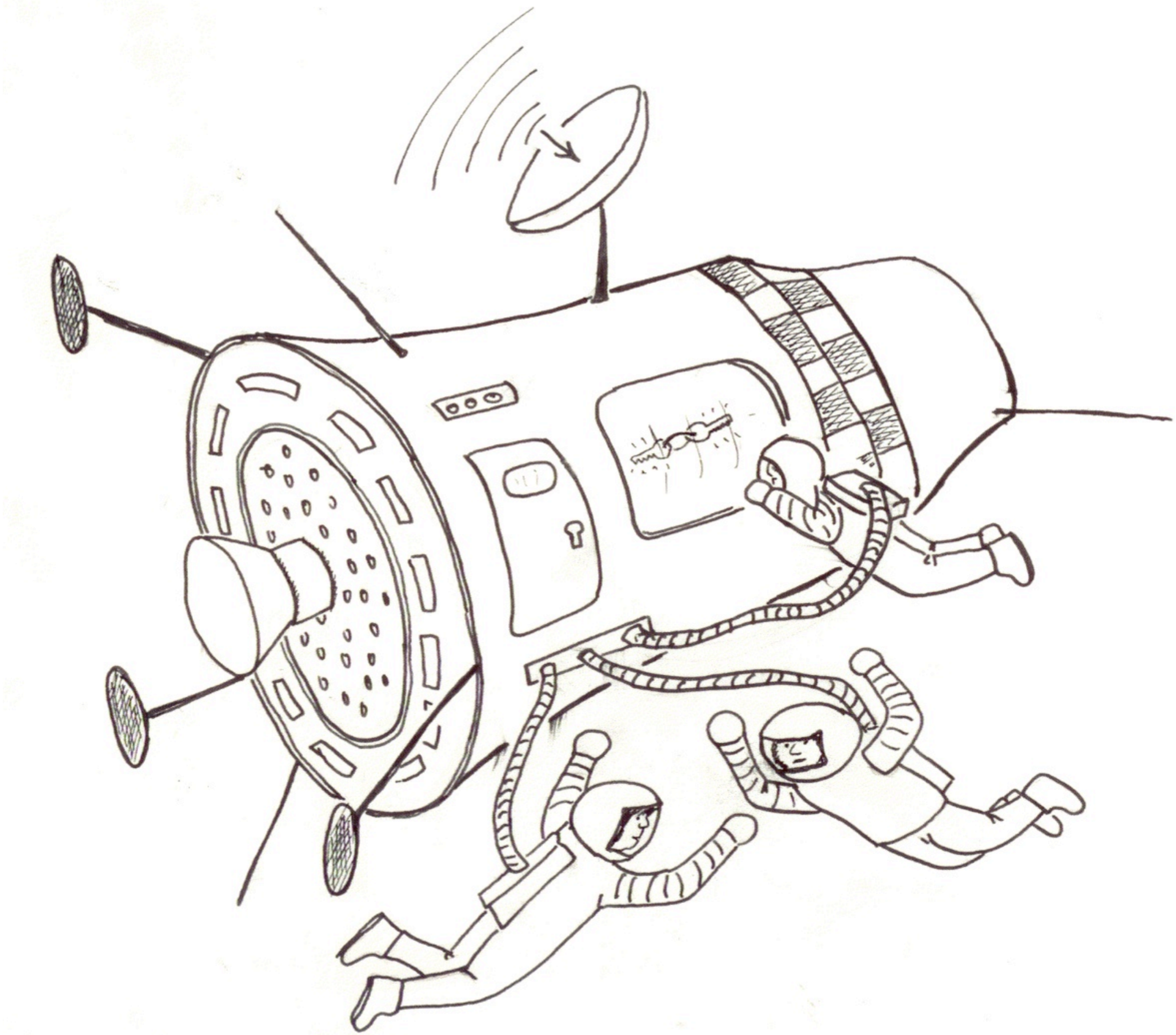
An insert/delete costs amortized O((log *N*)/B) per insert or delete

- A buffer flush costs O(1) & sends *B* elements down one level
- It costs O(1/*B*) to send element down one level of the tree.
- There are O(log *N*) levels in a tree.



Difficulty of Key Accesses

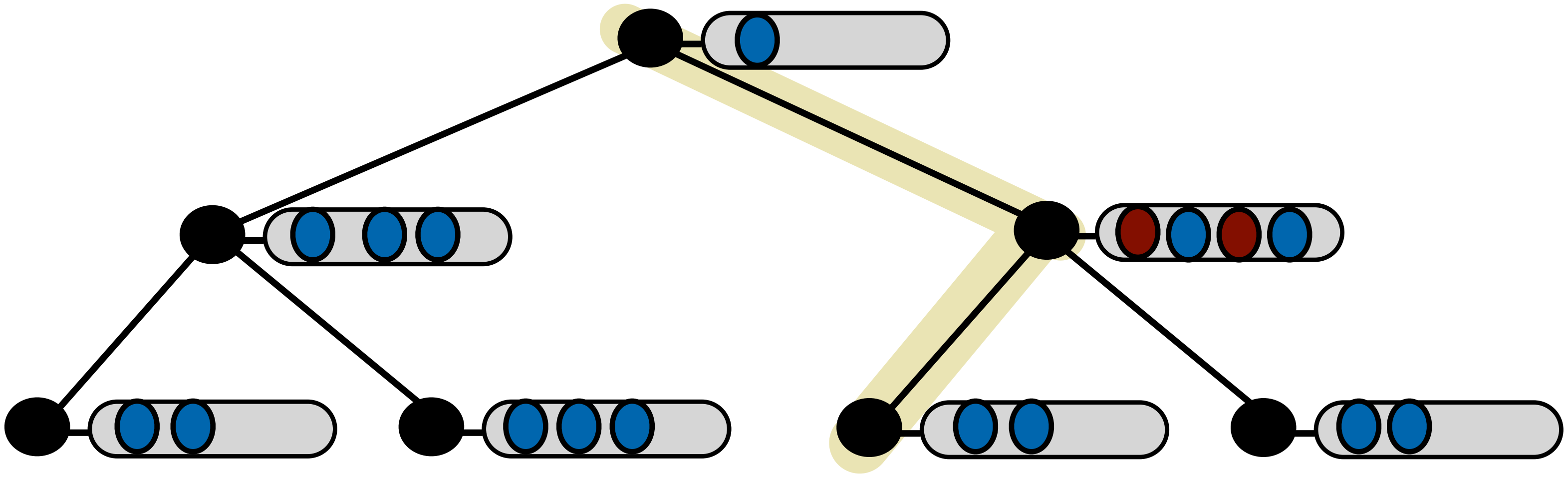
Difficulty of Key Accesses



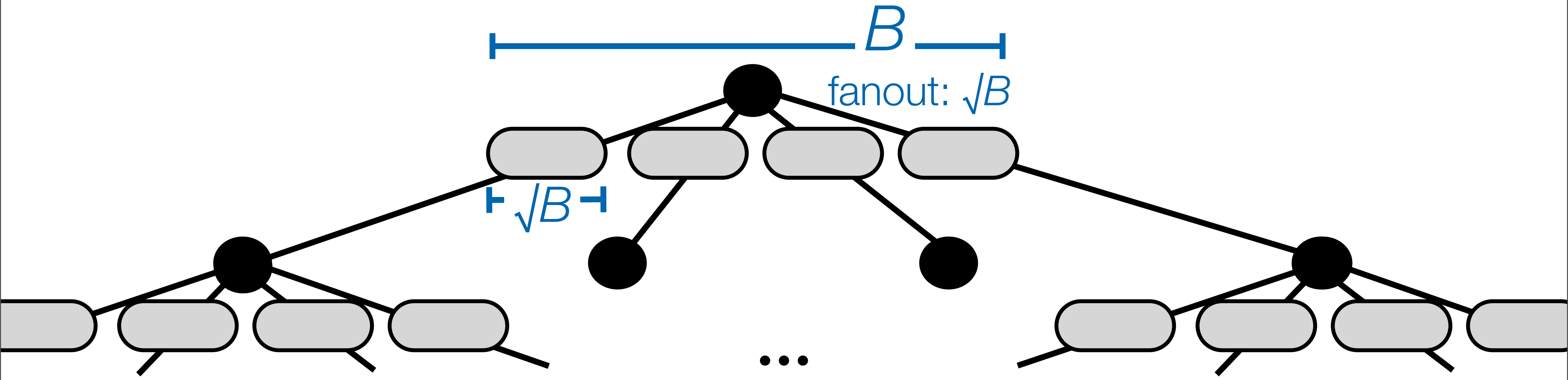
Analysis of point queries

To search:

- examine each buffer along a single root-to-leaf path.
- This costs O(log *N*).



Obtaining optimal point queries + very fast inserts



Point queries cost $O(\log_{\sqrt{B}} N) = O(\log_B N)$

- This is the tree height.

Inserts cost $O((\log_B N)/\sqrt{B})$

- Each flush cost O(1) I/Os and flushes $\sqrt{B}$ elements.

Cache-oblivious write-optimized structures

You can even make these data structures cache-oblivious.

[Bender, Farach-Colton, Fineman, Fogel, Kuszmaul, Nelson, SPAA 07]

[Brodal, Demaine, Fineman, Iacono, Langerman, Munro, SODA 10]

This means that the data structure can be made ***platform independent (no knobs)***, i.e., works simultaneously for all values of *B* and *M*.

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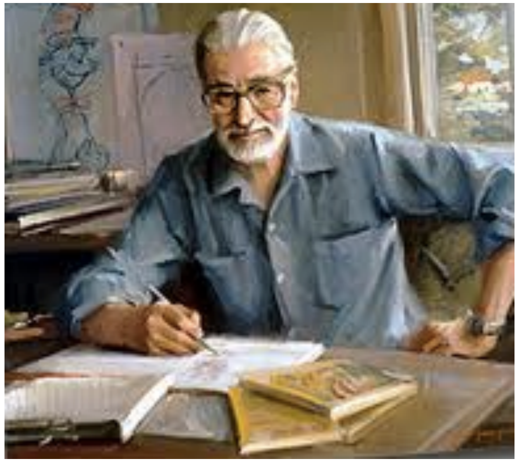
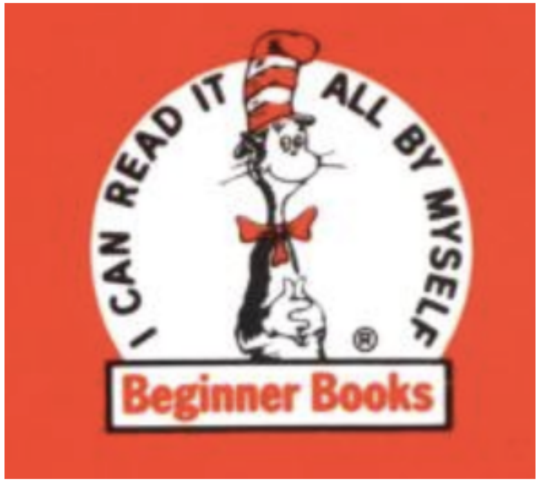
What the world looks like

Insert/point query asymmetry

- Inserts can be fast: >50K high-entropy writes/sec/disk.
- Point queries are necessarily slow: <200 high-entropy reads/sec/disk.

We are used to reads and writes having about the same cost, but writing is easier than reading.

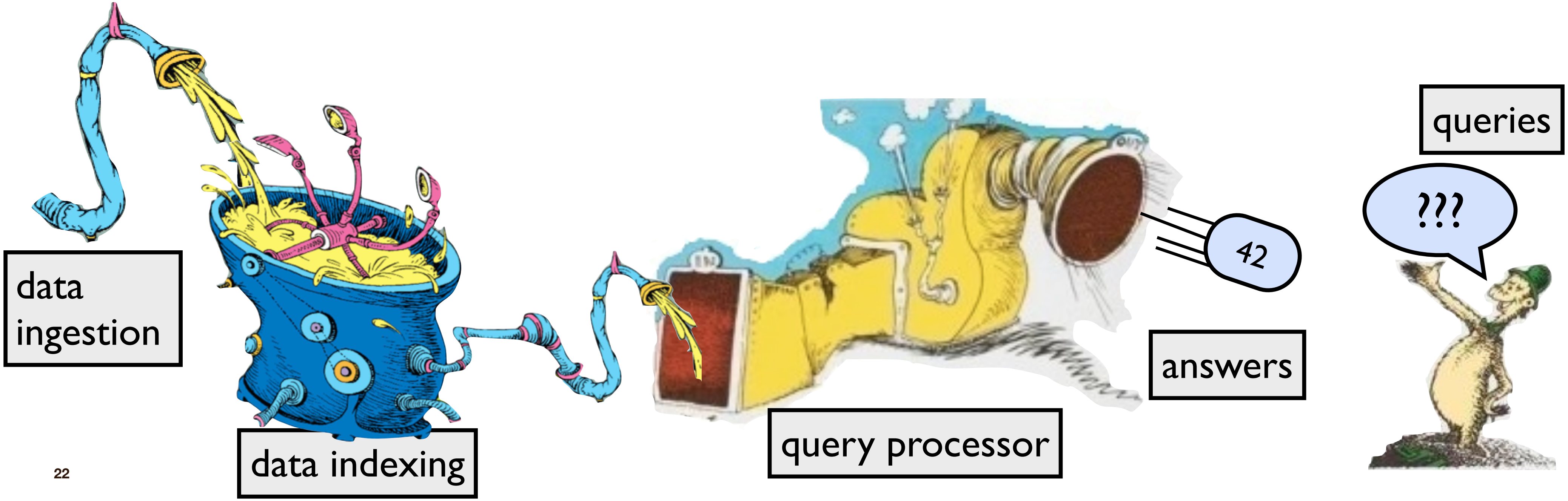




The right read-optimization is write-optimization

The right index makes queries run fast.

- Write-optimized structures maintain indexes efficiently.

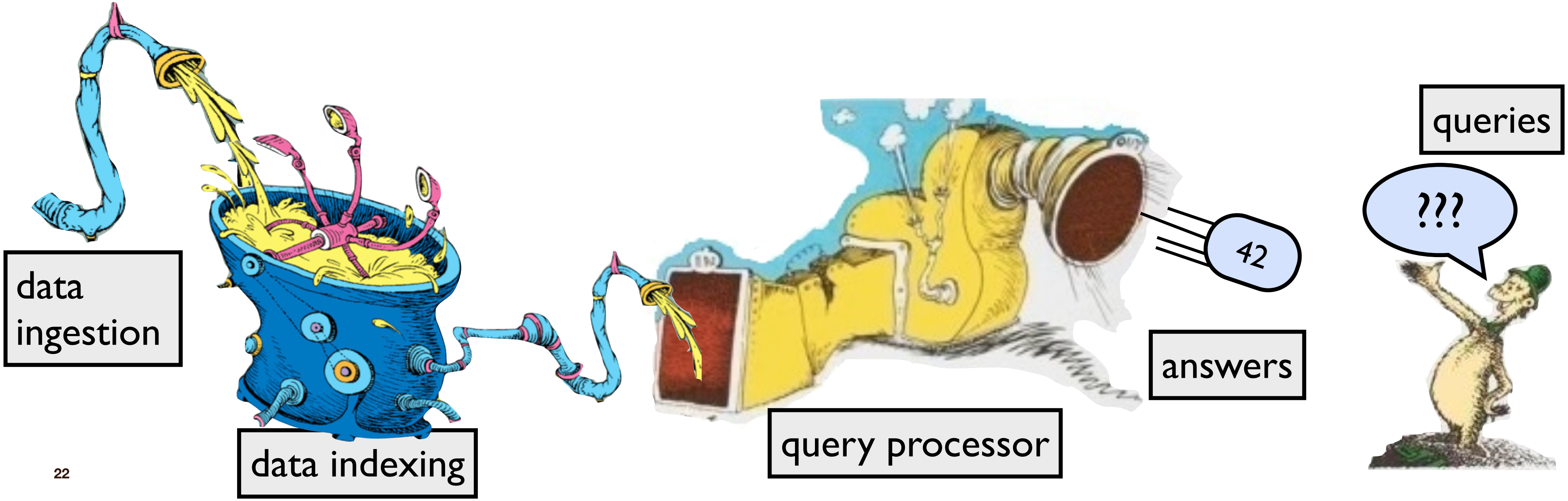


The right read-optimization is write-optimization

The right index makes queries run fast.

- Write-optimized structures maintain indexes efficiently.

Fast writing is a currency we use to accelerate queries. Better indexing means faster queries.



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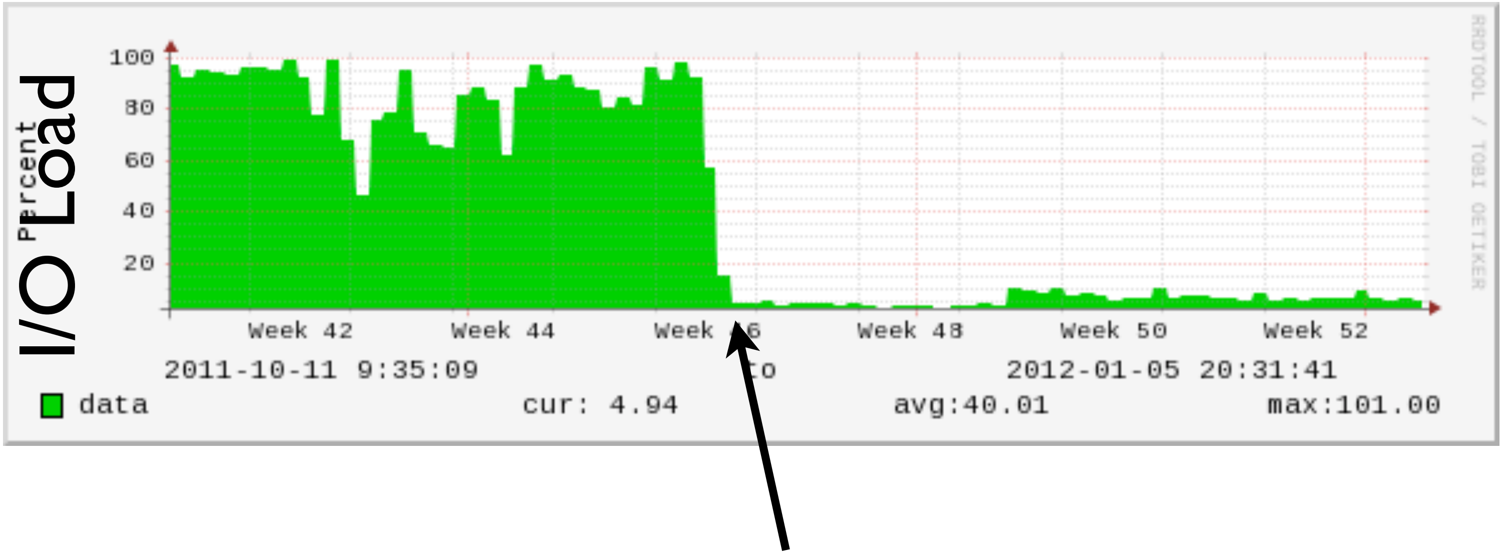
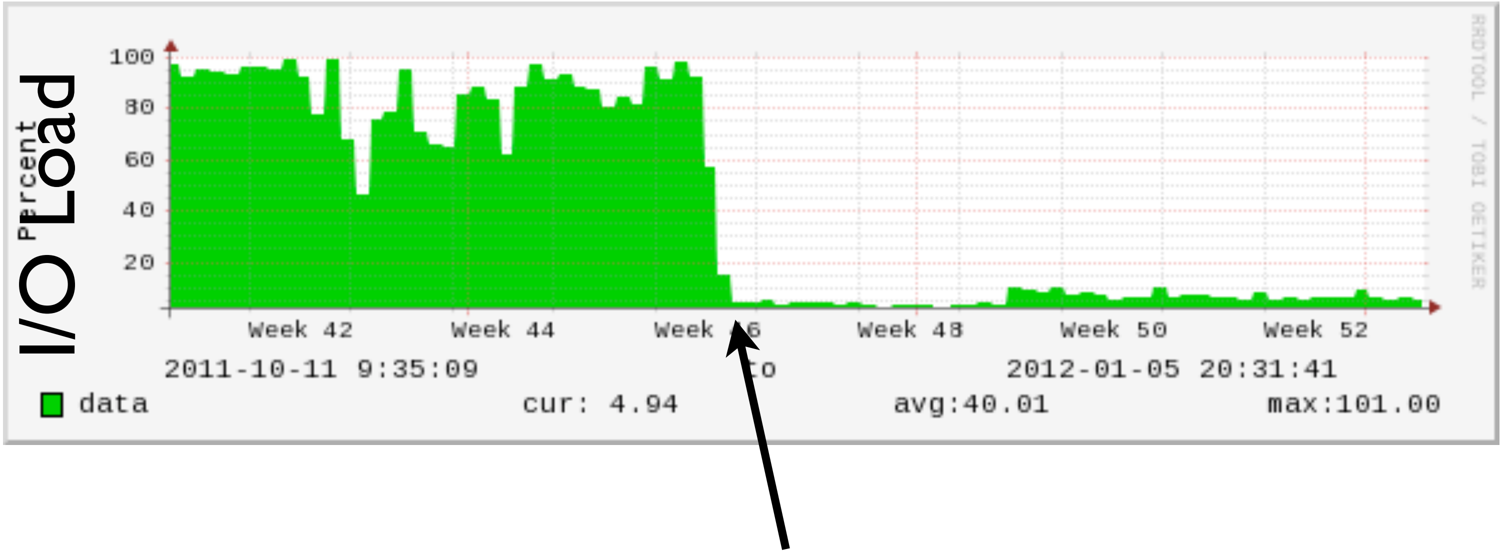


Add selective indexes.

(We can now afford to maintain them.)

The right read-optimization is write-optimization



Add selective indexes.

(We can now afford to maintain them.)

Write-optimized structures can significantly mitigate the insert/query/freshness tradeoff.

Implementation Issues

Write optimization. ✔ What's missing?

Optimal read-write tradeoff: Easy

Full featured: Hard

- Variable-sized rows
- Concurrency-control mechanisms
- Multithreading
- Transactions, logging, ACID-compliant crash recovery
- Optimizations for the special cases of sequential inserts and bulk loads
- Compression
- Backup

Systems often assume search cost = insert cost

Some inserts/deletes have hidden searches.

Example:

- return error when a duplicate key is inserted.
- return # elements removed on a delete.

These “cryptosearches” throttle insertions down to the performance of B-trees.

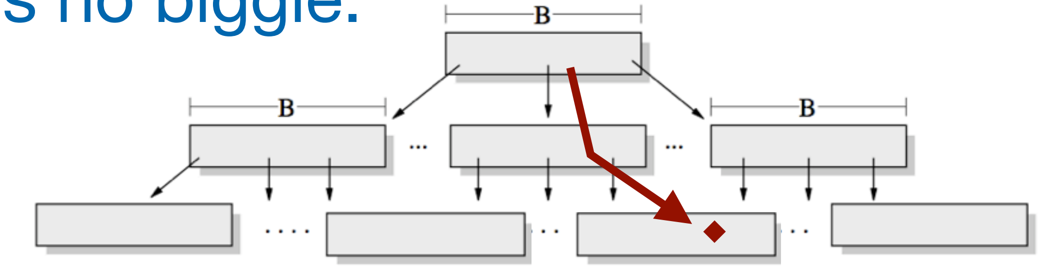
Cryptosearches in uniqueness checking

Uniqueness checking has a hidden search:

```
If Search(key) == True
    Return Error;
Else
    Fast_Insert(key,value);
```

In a B-tree uniqueness checking comes for free

- On insert, you fetch a leaf.
- Checking if key exists is no biggie.



Cryptosearches in uniqueness checking

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```
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```

In a write-optimized structure, that crypto-search can throttle performance

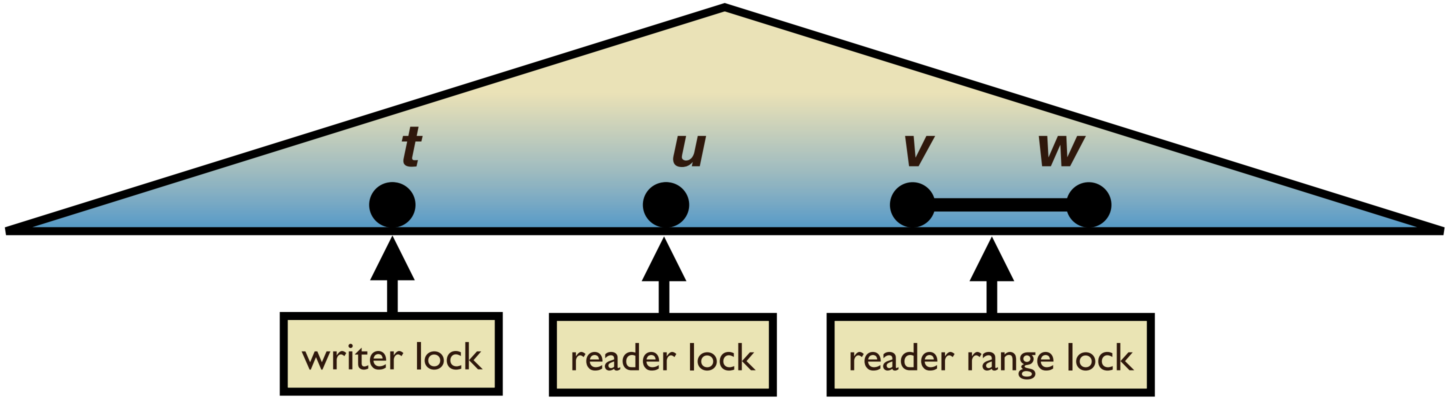
- Insertion messages are injected.
- These eventually get to “bottom” of structure.
- Insertion w/Uniqueness Checking 100x slower.
- Bloom filters, Cascade Filters, etc help.

[Bender, Farach-Colton, Johnson, Kraner, Kuszmaul, Medjedovic, Montes, Shetty, Spillane, Zadok 12]

A locking scheme with cryptosearches

A simple implementation of pessimistic locking: maintain locks in leaves

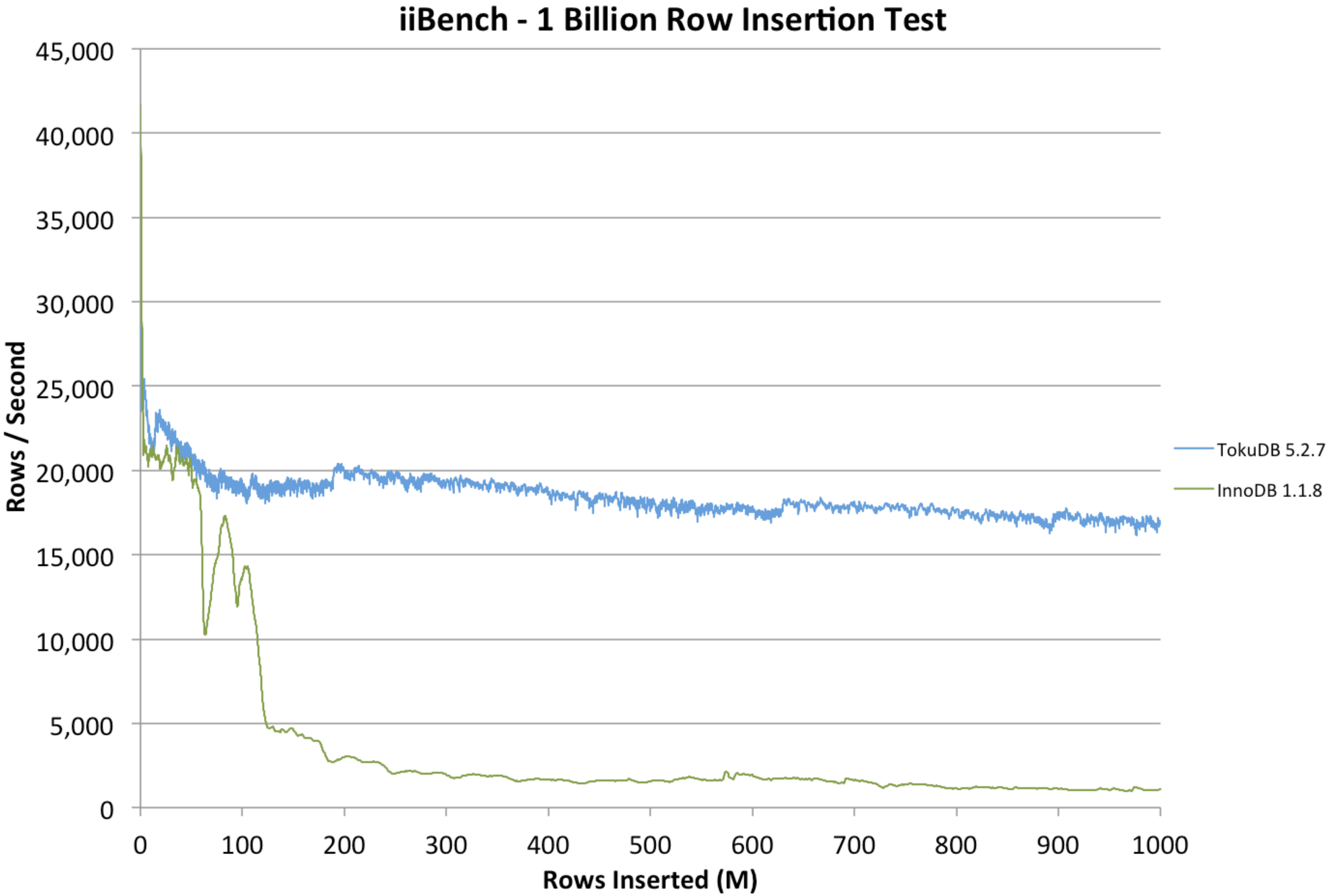
- Insert row ***t***
- Search for row ***u***
- Search for row ***v*** and put a cursor
- Increment cursor. Now cursor points to row ***w***.



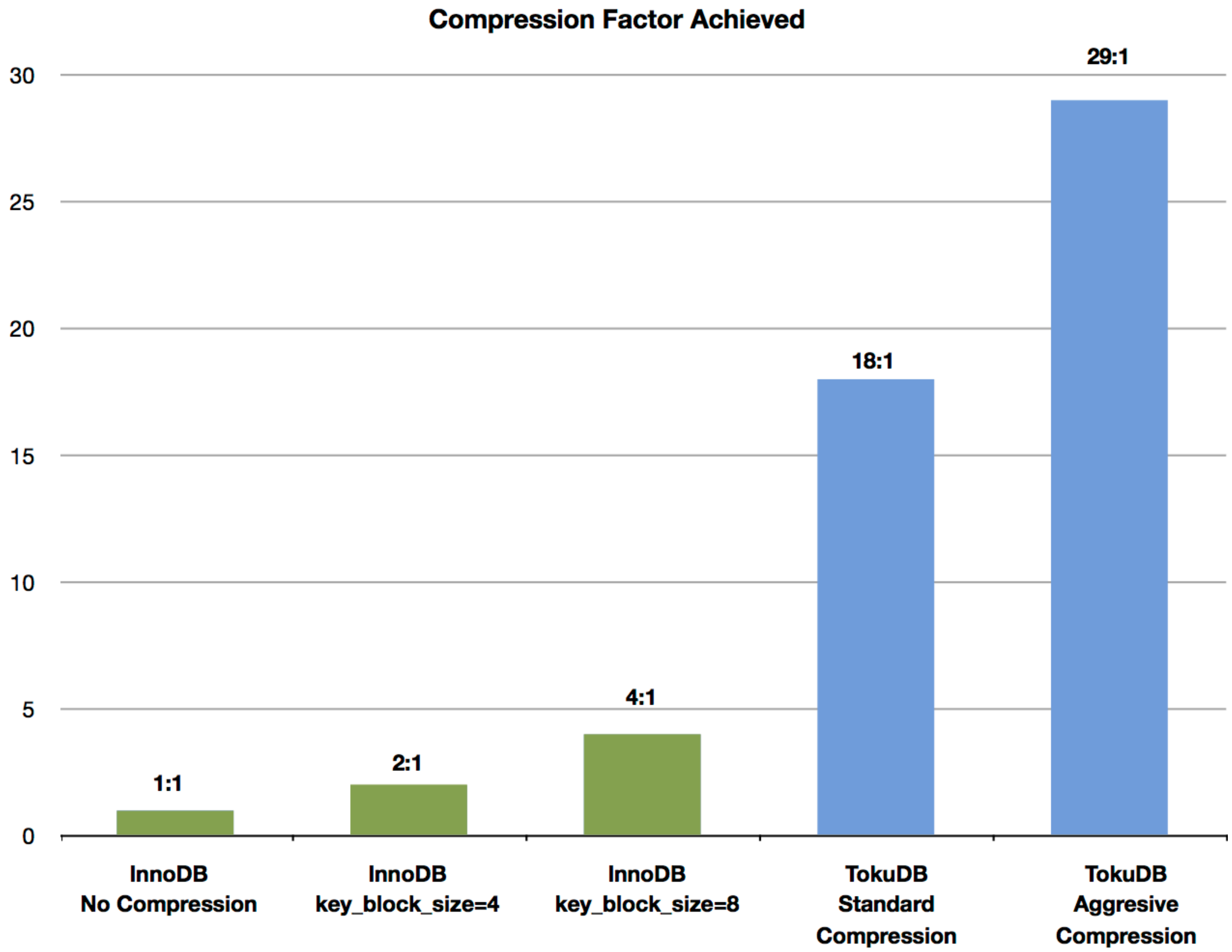
This scheme is inefficient for write-optimized structures because there are cryptosearches on writes.

Performance

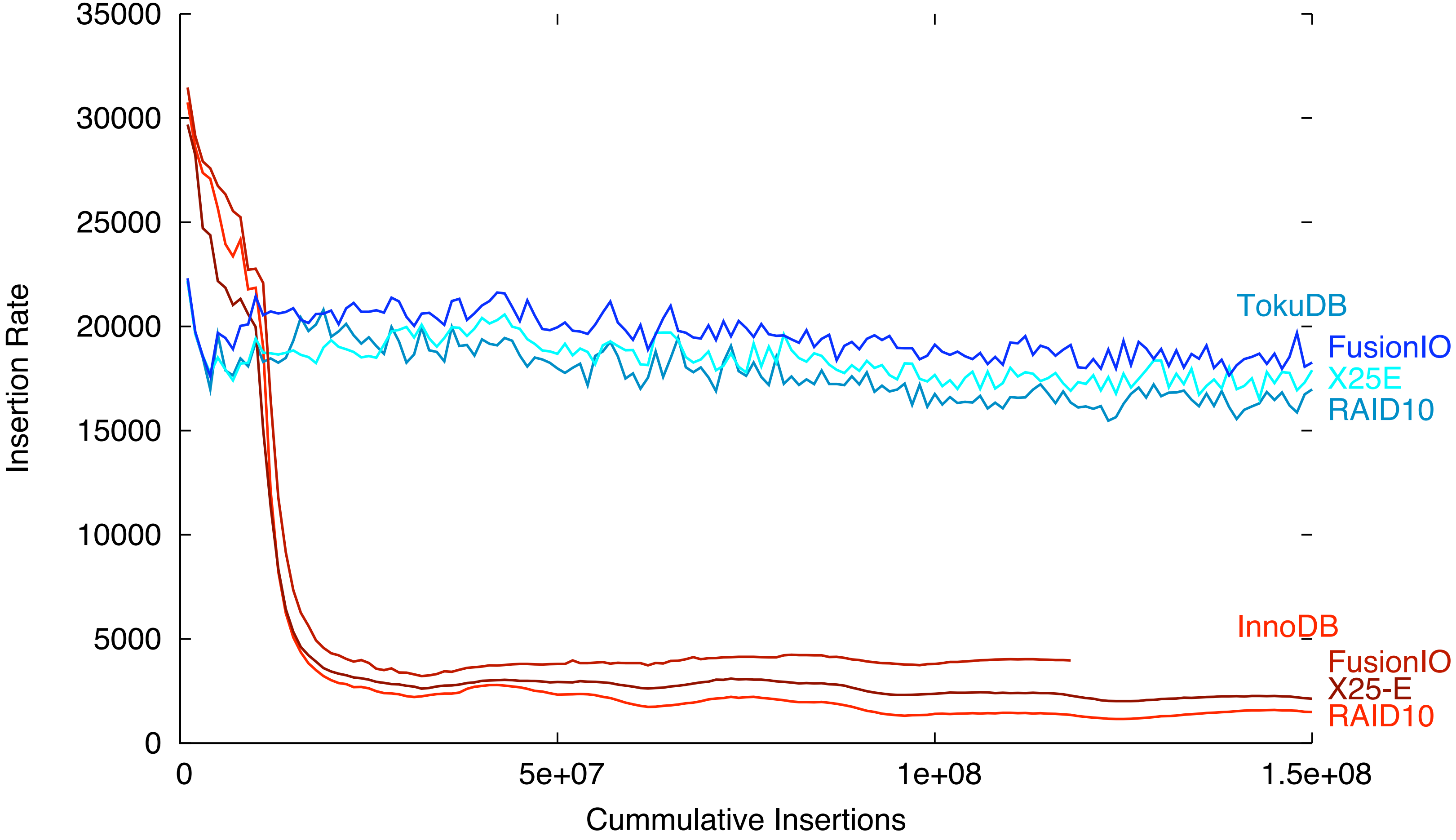
iiBench Insertion Benchmark



Compression



iiBench on SSD



TokuDB on rotating disk beats InnoDB on SSD.

Write-optimization Can Help Schema Changes

InnoDB
Index Creation

00:31:34 → 00:00:02

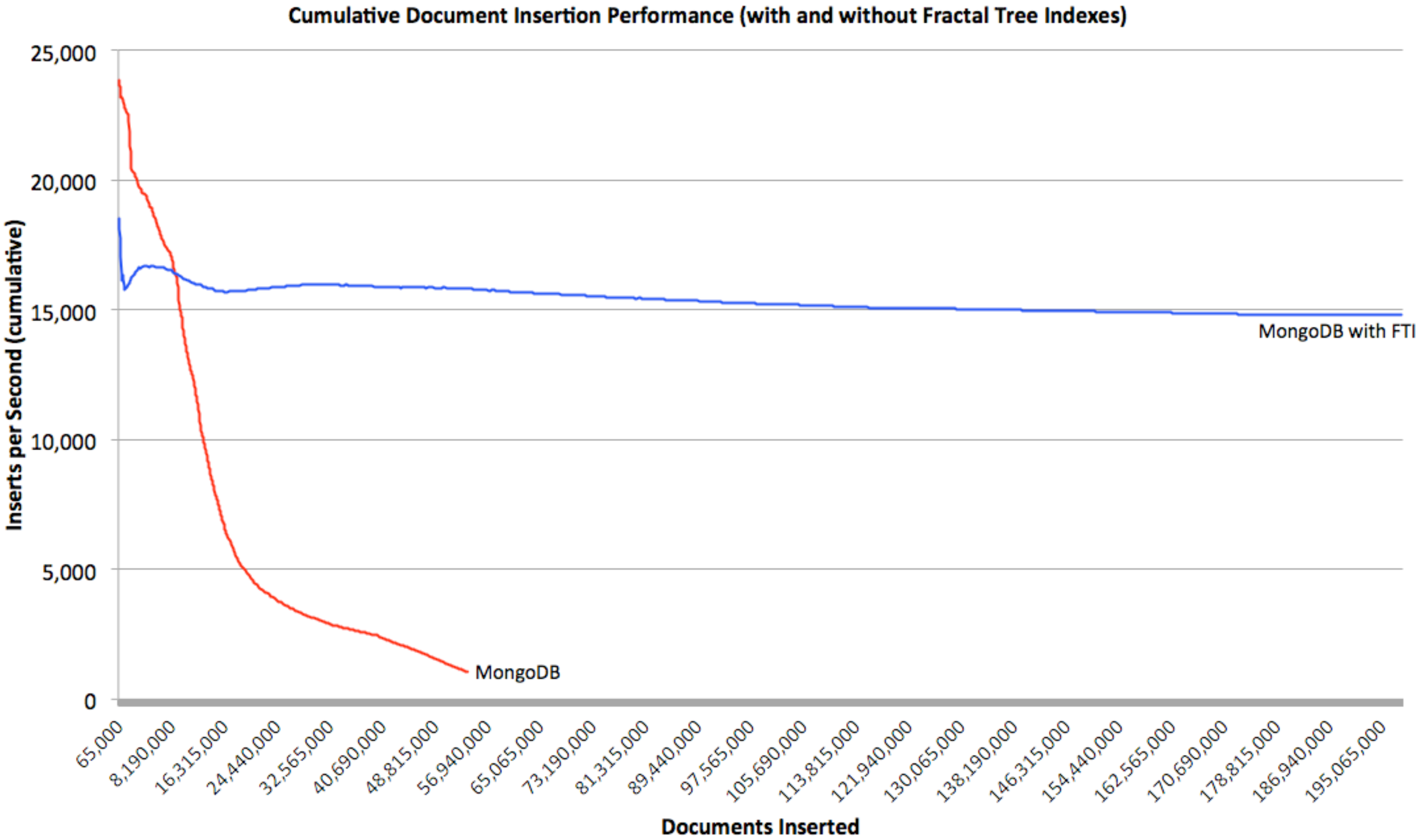
TokuDB
Hot Indexing

InnoDB
Column Addition

17:44:41 → 00:00:03

TokuDB
Hot Column Addition

MongoDB with Fractal-Tree Index



Scaling into the Future

Write-optimization going forward

Example: Time to fill a disk in 1973, 2010, 2022.

- log high-entropy data sequentially versus index data in B-tree.

Year	Size	Bandwidth	Access Time	Time to log data on disk	Time to fill disk using a B-tree (row size 1K)
1973	35MB	835KB/s	25ms	39s	975s
2010	3TB	150MB/s	10ms	5.5h	347d
2022	220TB	1.05GB/s	10ms	2.4d	70y

Better data structures may be a luxury now, but they will be essential by the decade's end.

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* Projected times for fully multi-threaded version

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---

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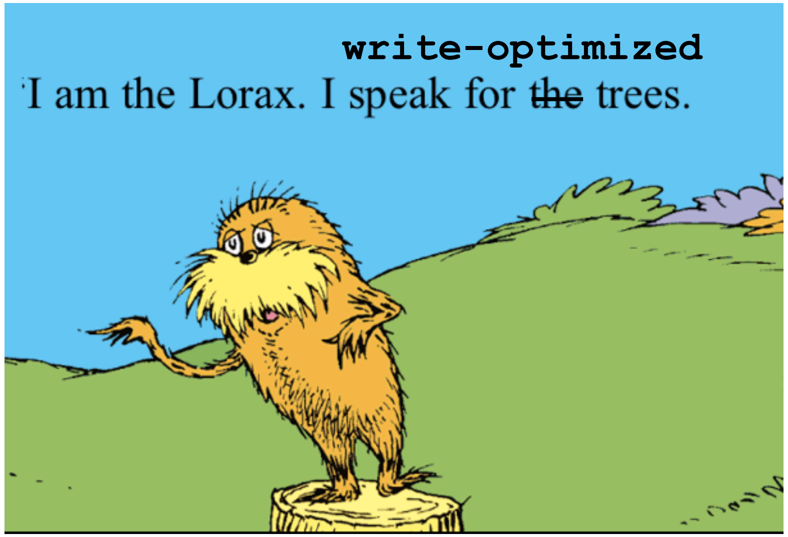
Summary of Module

Write-optimization can solve many problems.

- There is a provable point-query insert tradeoff. We can insert 10x-100x faster without hurting point queries.
- We can avoid much of the funny tradeoff between data ingestion, freshness, and query speed.
- We can avoid tuning knobs.



Data Structures and Algorithms for Big Data
Module 3: (Case Study)
TokuFS--How to Make a Write-Optimized File System

Michael A. Bender
Stony Brook & Tokutek

Bradley C. Kuszmaul
MIT & Tokutek

STONY BROOK
STATE UNIVERSITY OF NEW YORK

Tokutek®

Story for Module

Algorithms for Big Data apply to all storage systems, not just databases.

Some big-data users store use a file system.

The problem with Big Data is Microdata...

HEC FSIO Grand Challenges

Store 1 trillion files

Create tens of thousands of files per second

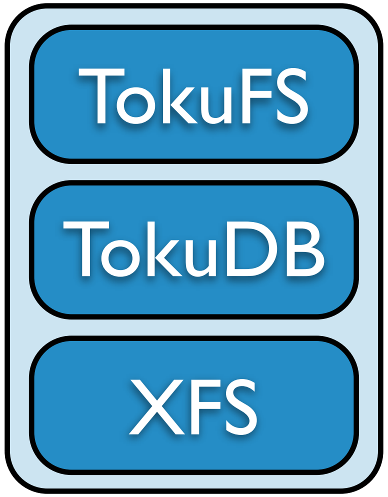
Traverse directory hierarchies fast (`ls -R`)

B-trees would require at least hundreds of disk drives.

TokuFS

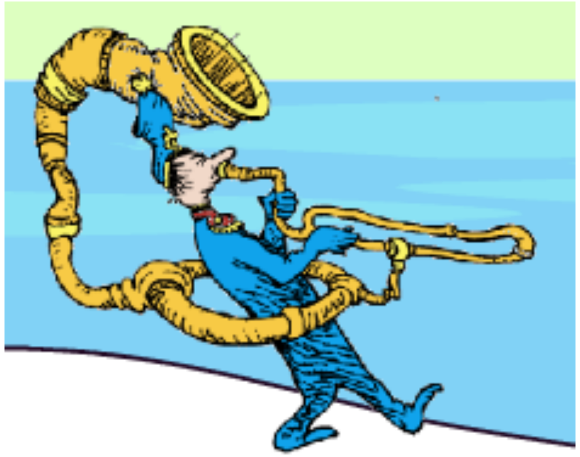
TokuFS [Esmet, Bender, Farach-Colton, Kuszmaul HotStorage12]

- A file-system prototype
- >20K file creates/sec
- very fast `ls -R`
- HEC grand challenges on a cheap disk (except 1 trillion files)


TokuFS

TokuDB

XFS



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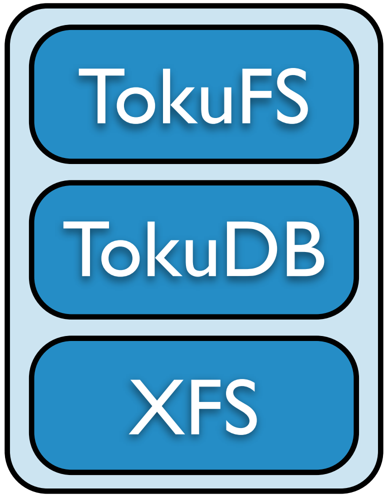
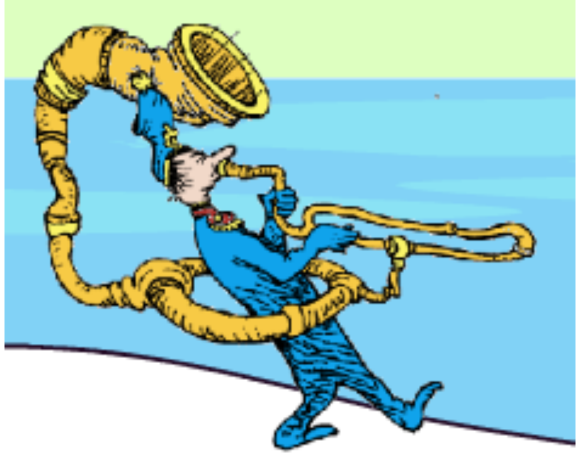


- A file-system prototype
- >20K file creates/sec
- very fast `ls -R`
- HEC grand challenges on a cheap disk (except 1 trillion files)

- TokuFS offers orders-of-magnitude speedup on *microdata* workloads.
  - Aggregates microwrites while indexing.
  - So it can be faster than the underlying file system.



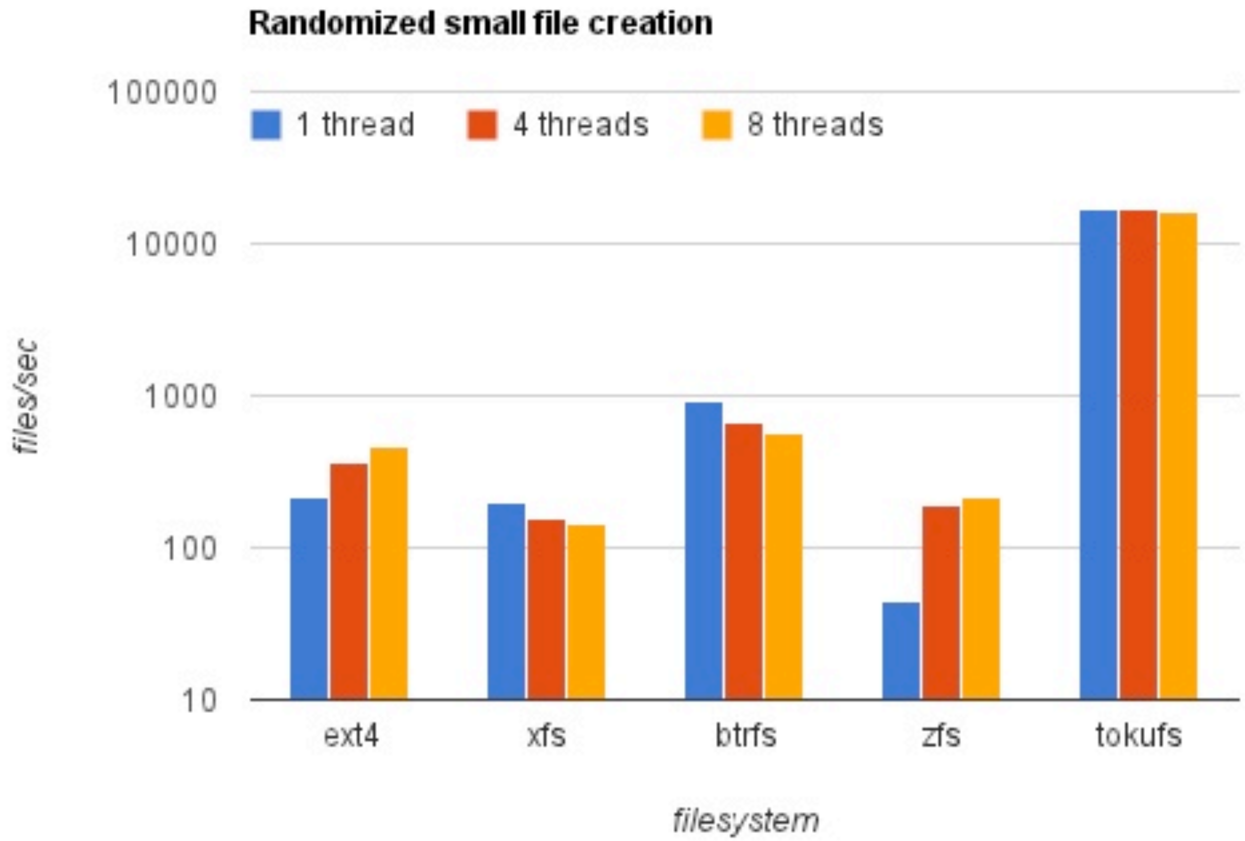
Big speedups on microwrites

We ran microdata-intensive benchmarks

- Compared TokuFS to ext4, XFS, Btrfs, ZFS.
- Stressed metadata and file data.
- Used commodity hardware:
    - 2 core AMD, 4GB RAM
    - Single 7200 RPM disk
    - Simple, cheap setup. No hardware tricks.
- In all tests, we observed orders of magnitude speed up.

Faster on small file creation

Create 2 million 200-byte files in a shallow tree



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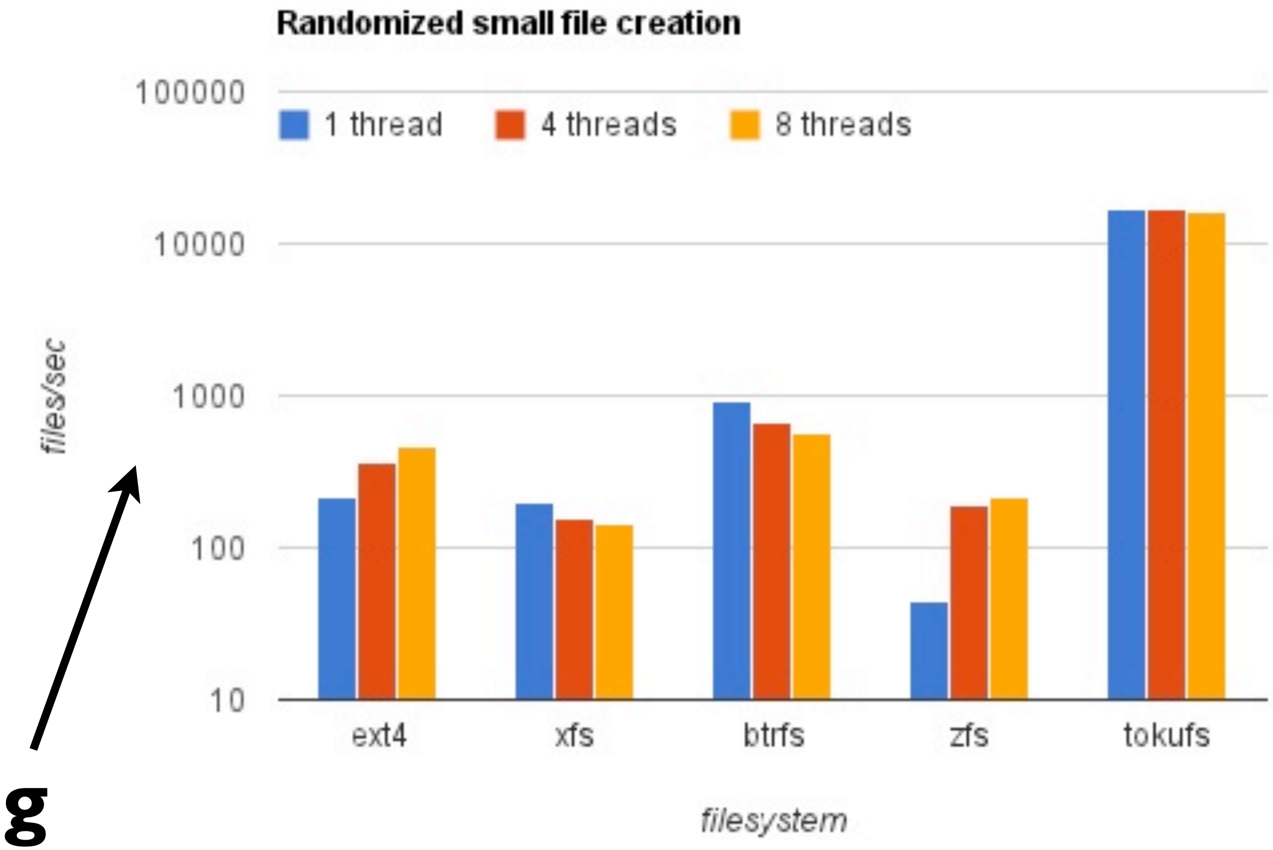
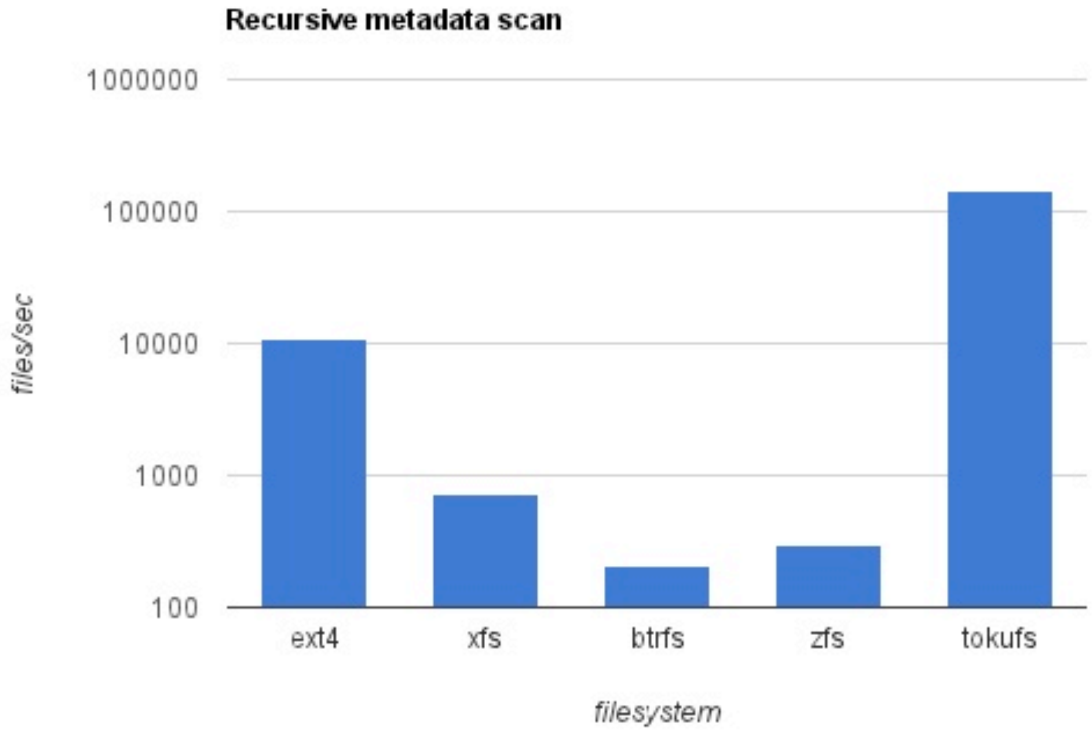


Log scale

Faster on metadata scan

Recursively scan directory tree for metadata

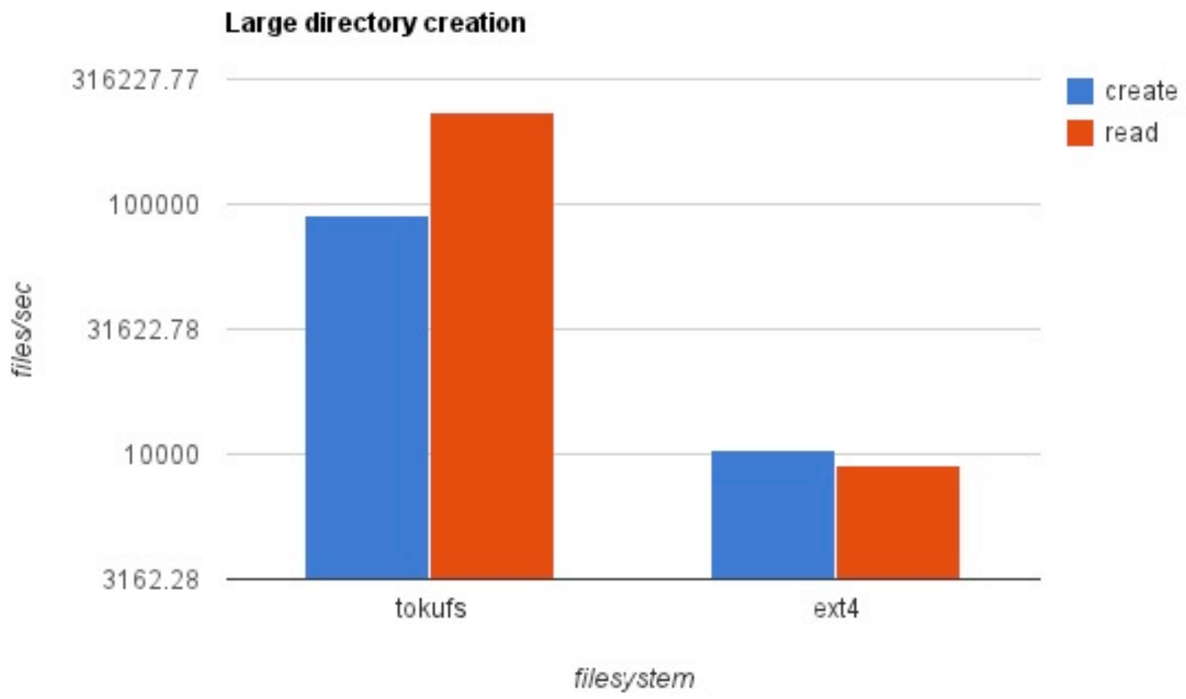
- Use the same 2 million files created before.
- Start on a cold cache to measure disk I/O efficiency



Faster on big directories

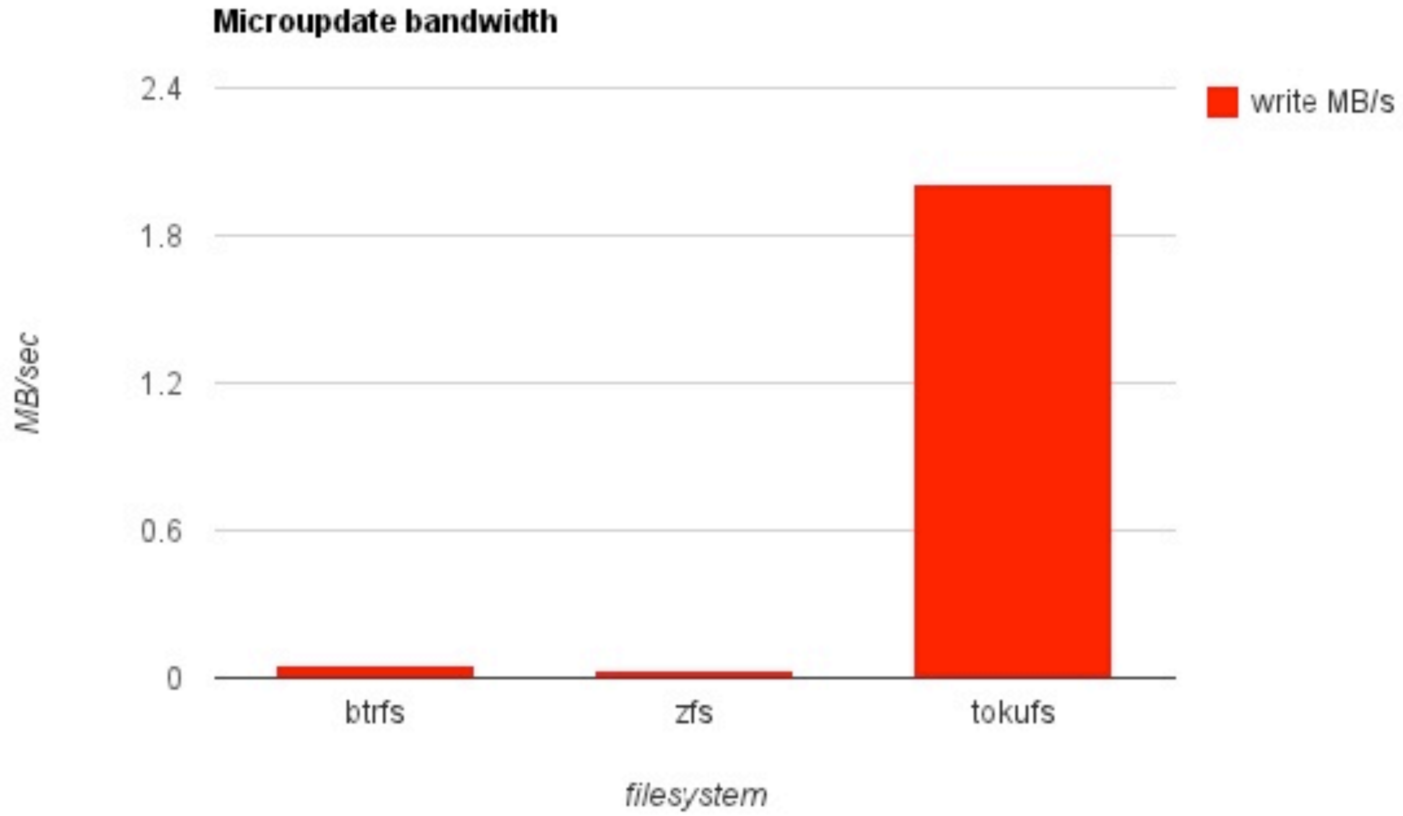
Create one million empty files in a directory

- Create files with random names, then read them back.
- Tests how well a single directory scales.



Faster on microwrites in a big file

Randomly write out a file in small, unaligned pieces



TokuFS
Implementation

TokuFS employs two indexes

Metadata index:

- The metadata index maps pathname to file metadata.
  - /home/esmet ⟹ mode, file size, access times, ...
  - /home/esmet/tokufs.c ⟹ mode, file size, access times, ...

Data index:

- The data index maps pathname, blocknum to bytes.
  - /home/esmet/tokufs.c, 0 ⟹ [block of bytes]
  - /home/esmet/tokufs.c, 1 ⟹ [block of bytes]
- Block size is a compile-time constant: 512.
  - good performance on small files, moderate on large files

Common queries exhibit locality

Metadata index keys: full path as string

- All the children of a directory are contiguous in the index
- Reading a directory is simple and fast

Data block index keys: 【full path, blocknum】

- So all the blocks for a file are contiguous in the index
- Reading a file is simple and fast

TokuFS compresses indexes

Reduces overhead from full path keys

- Pathnames are highly “prefix redundant”
- They compress very, very well in practice

Reduces overhead from zero-valued padding

- Uninitialized bytes in a block are set to zero
- Good portions of the metadata struct are set to zero

Compression between 7-15x on real data

- For example, a full MySQL source tree

TokuFS is fully functional

TokuFS is a prototype, but fully functional.

- Implements files, directories, metadata, etc.
- Interfaces with applications via shared library, header.

We wrote a FUSE implementation, too.

- FUSE lets you implement filesystems in user space.
- But there's overhead, so performance isn't optimal.
- The best way to run is through our POSIX-like file API.

Microdata is the Problem

Data Structures and Algorithms for Big Data

Module 4: Paging

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Stony Brook & Tokutek

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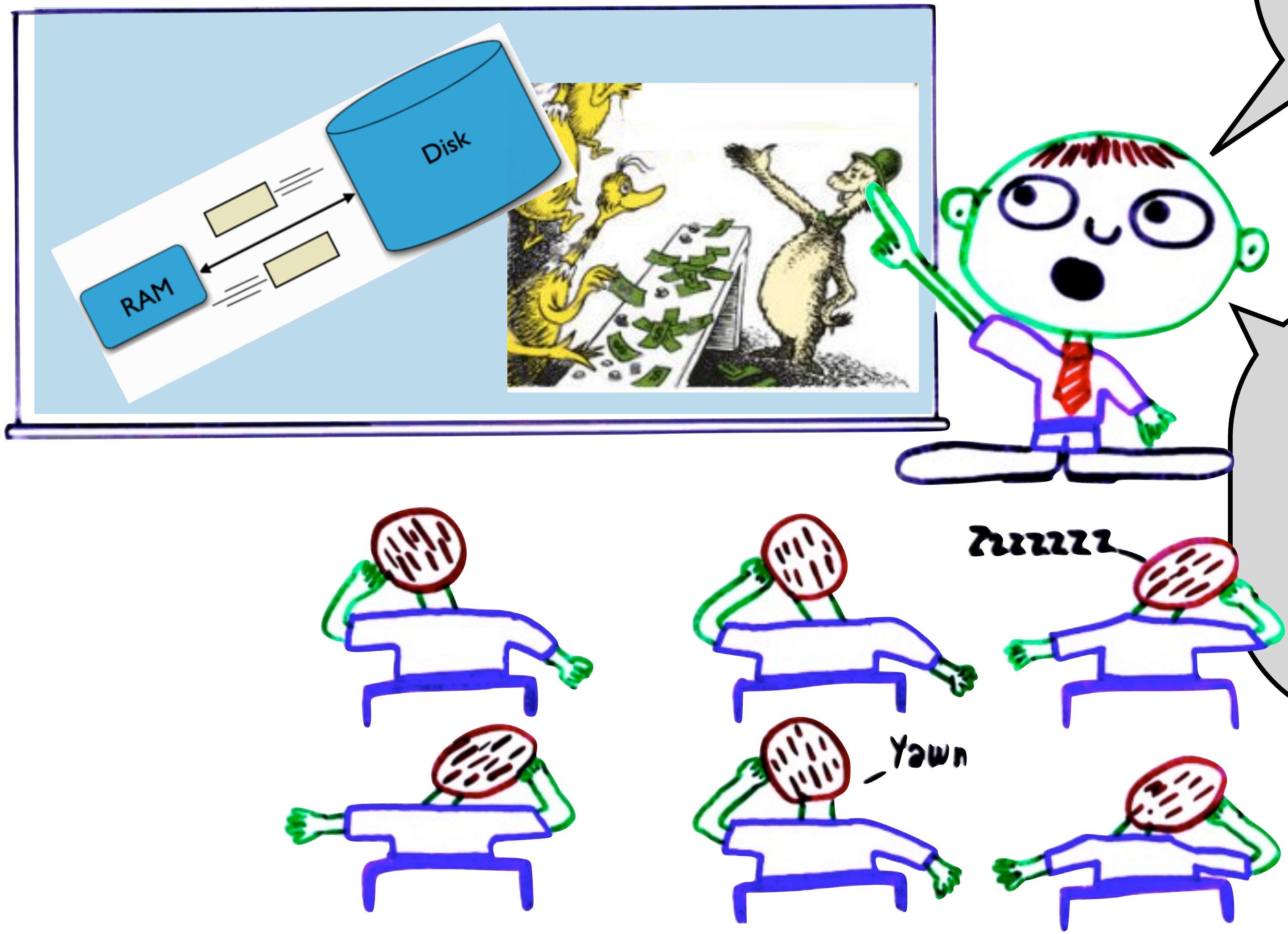
MIT & Tokutek

This Module



The algorithmics of cache-management.

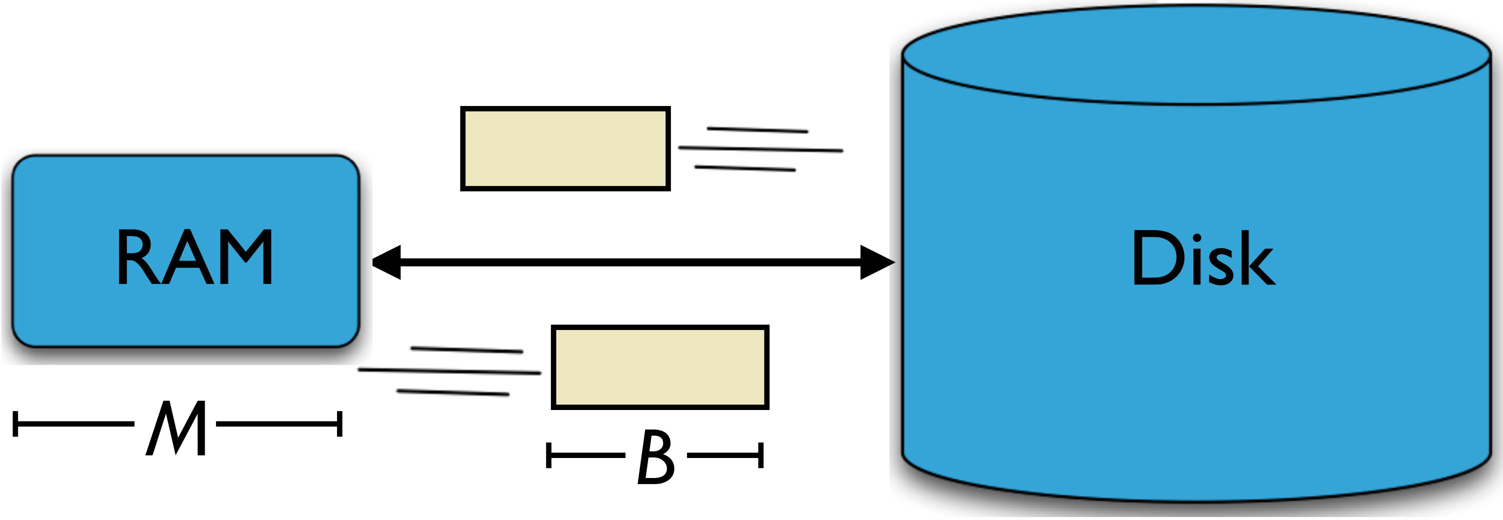
This will help us understand I/O- and cache-efficient algorithms.

Recall Disk Access Model

Goal: minimize # block transfers.

- Data is transferred in blocks between RAM and disk.
- Performance bounds are parameterized by B, M, N.

When a block is cached, the access cost is 0. Otherwise it's 1.



[Aggarwal+Vitter '88]

Recall Cache-Oblivious Analysis

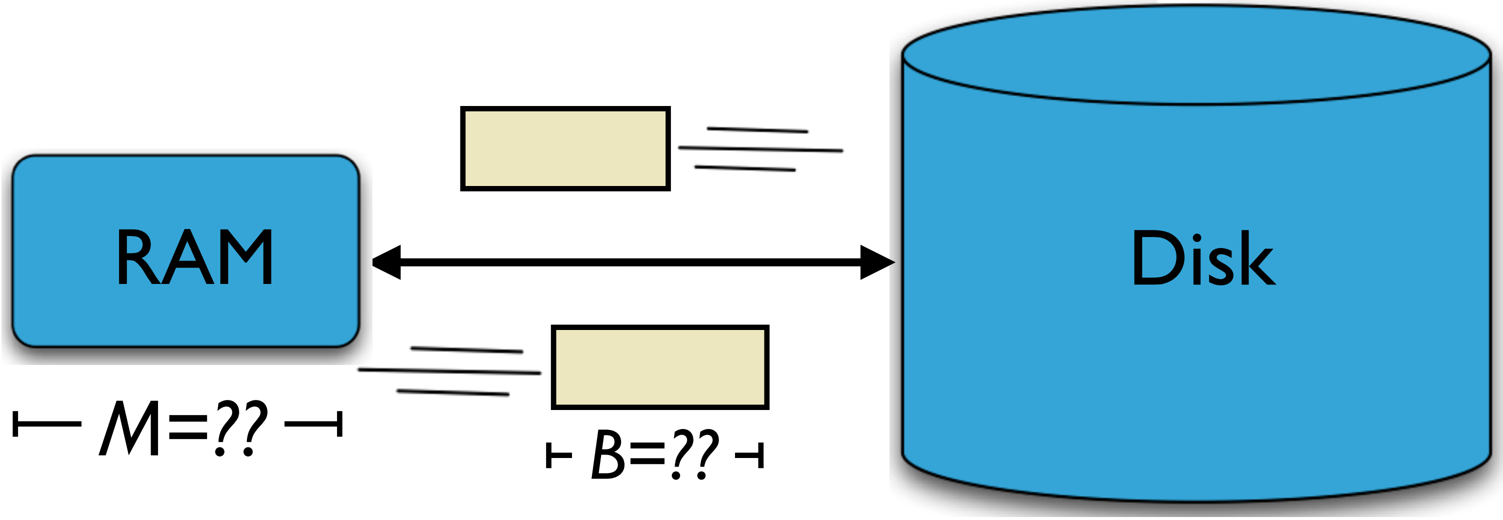
Disk Access Model (DAM Model):

- Performance bounds are parameterized by *B*, *M*, *N*.

Goal: Minimize # of block transfers.

Beautiful restriction:

- Parameters *B*, *M* are unknown to the algorithm or coder.



[Frigo, Leiserson, Prokop, Ramachandran ’99]

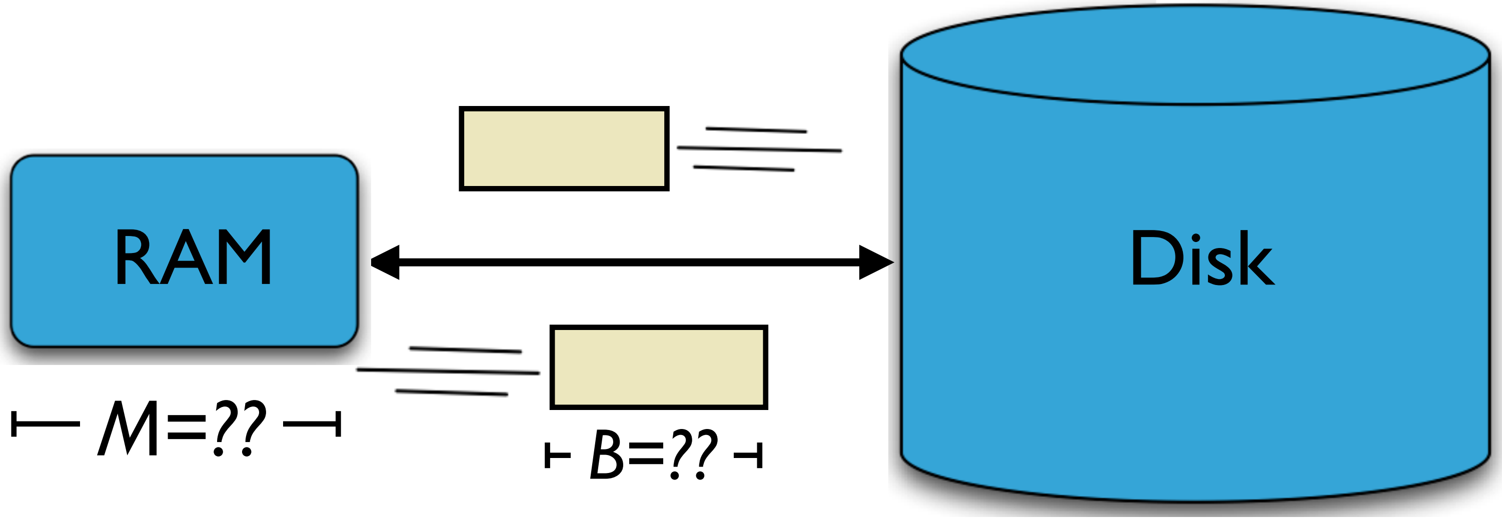
Recall Cache-Oblivious Analysis

CO analysis applies to unknown multilevel hierarchies:

- Cache-oblivious algorithms work for all *B* and *M*...
- ... and all levels of a multi-level hierarchy.

Moral:

- It's better to optimize approximately for all *B*, *M* rather than to try to pick the best *B* and *M*.

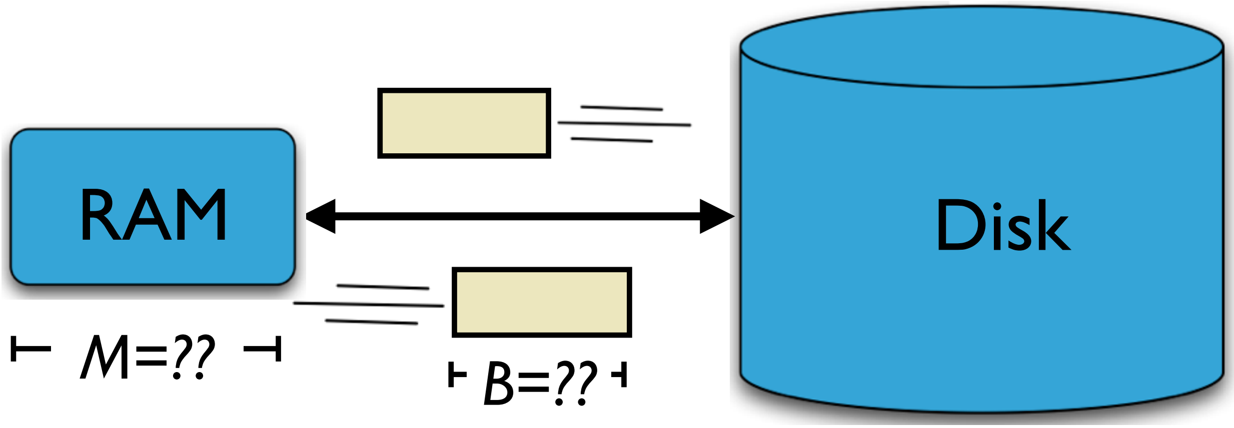


[Frigo, Leiserson, Prokop, Ramachandran '99]

Cache-Replacement in Cache-Oblivious Algorithms

Which blocks are currently cached in RAM?

- The system performs its own caching/paging.
- If we knew *B* and *M* we could explicitly manage I/O. (But even then, what should we do?)

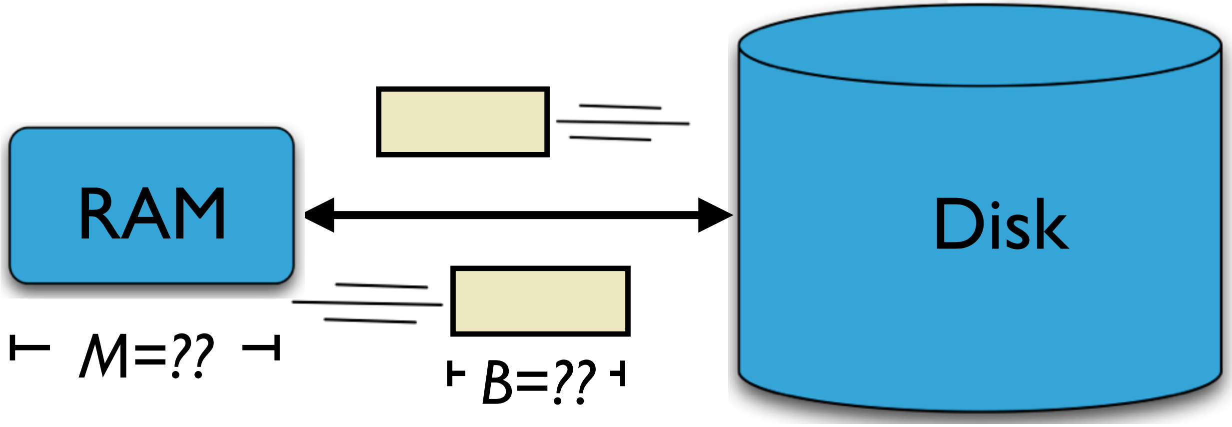


Cache-Replacement in Cache-Oblivious Algorithms

Which blocks are currently cached in RAM?

- The system performs its own caching/paging.
- If we knew B and M we could explicitly manage I/O. (But even then, what should we do?)

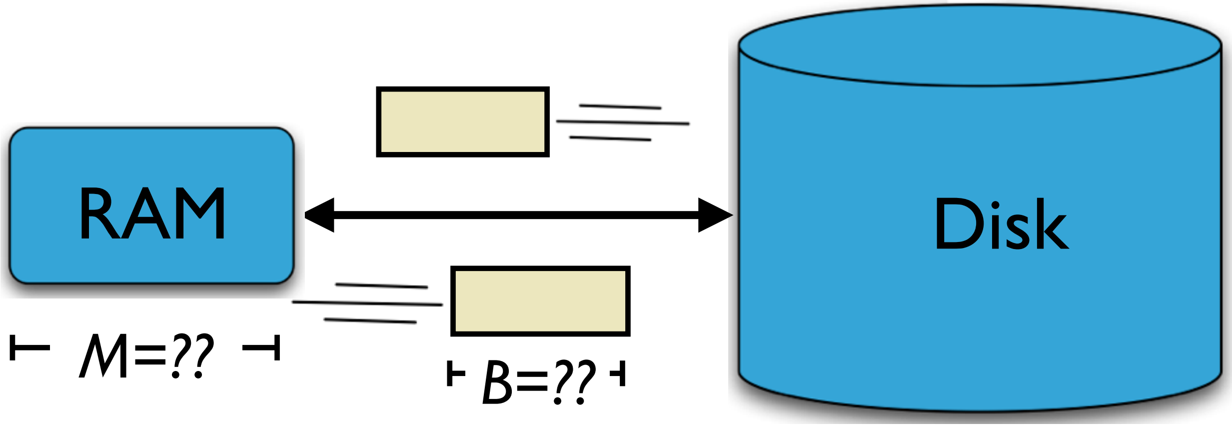
But systems may use different mechanisms, so what can we actually assume?



This Module: Cache-Management Strategies

With cache-oblivious analysis, we can assume a memory system with optimal replacement.

Even though the system manages memory, we can assume all the advantages of explicit memory management.



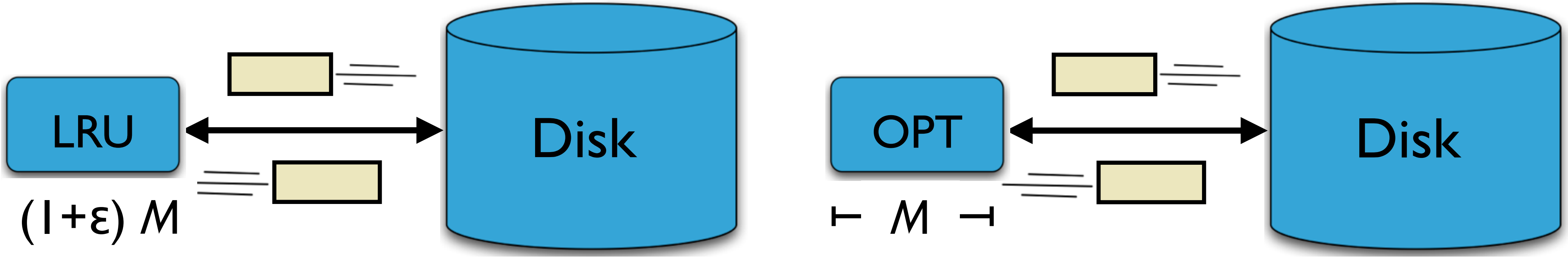
This Module: Cache-Management Strategies

An LRU-based system with memory *M* performs cache-management < 2x worse than the optimal, prescient policy with memory *M*/2.

Achieving optimal cache-management is hard because predicting the future is hard.

But LRU with (1+ε)*M* memory is almost as good (or better), than the optimal strategy with *M* memory.

[Sleator, Tarjan 85]



LRU with (1+ε) more memory is nearly as good or better...

... than OPT.

The paging/caching problem

A *program* is just sequence of block requests:

$$r_1, r_2, r_3, \ldots$$

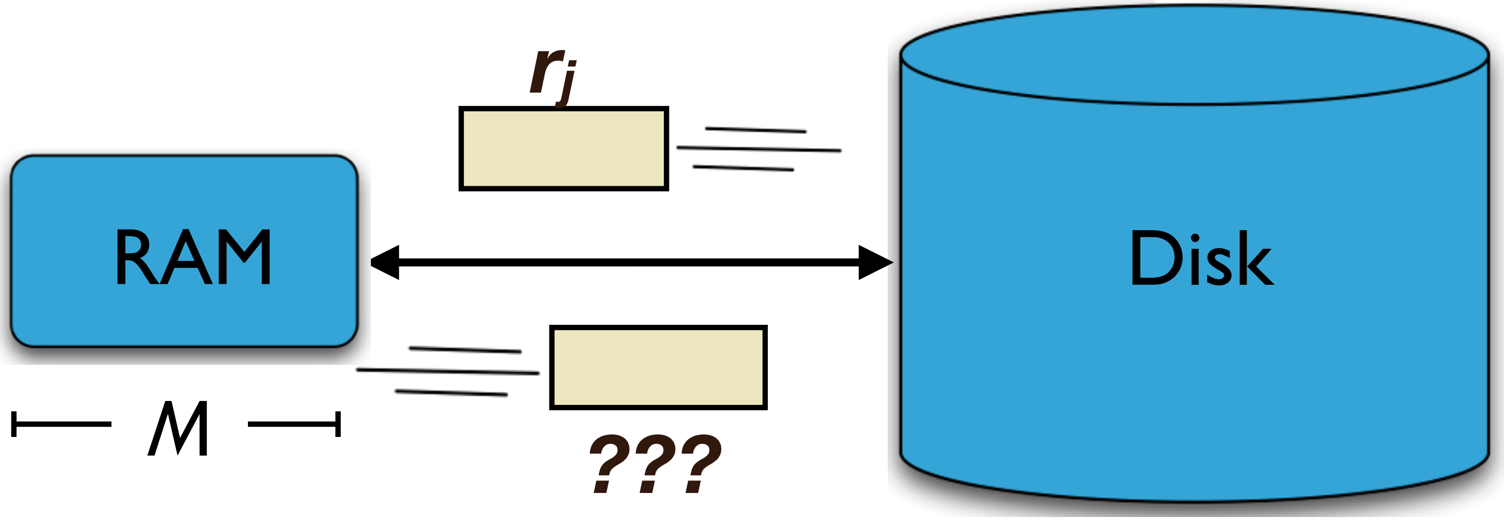
Cost of request *r_j*

$$\text{cost}(r_j) = \begin{cases} 0 & \text{block } r_j \text{ is already cached,} \\ 1 & \text{block } r_j \text{ is brought into cache.} \end{cases}$$

The paging/caching problem

RAM holds only *k=M/B* blocks.

Which block should be ejected when block r_j is brought into cache?



Paging Algorithms

LRU (least recently used)

- Discard block whose most recent access is earliest.

FIFO (first in, first out)

- Discard the block brought in longest ago.

LFU (least frequently used)

- Discard the least popular block.

Random

- Discard a random block.

LFD (longest forward distance)=OPT [Belady 69]

- Discard block whose next access is farthest in the future.

Optimal Page Replacement

LFD (Longest Forward Distance) [Belady ’69]**:**

- Discard the block requested farthest in the future.

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Cons: Who knows the Future?!

Optimal Page Replacement

LFD (Longest Forward Distance) [Belady ’69]**:**

- Discard the block requested farthest in the future.

Cons: Who knows the Future?!

Pros: LFD can be viewed as a point of comparison with online strategies.

Competitive Analysis

An online algorithm *A* is *k-competitive*, if for every request sequence *R*:

$$\text{cost}_A(R) \leq k\,\text{cost}_{\text{opt}}(R)$$

Idea of competitive analysis:

- The optimal (prescient) algorithm is a yardstick we use to compare online algorithms.

LRU is no better than k-competitive

Memory holds 3 blocks

$$M/B = k = 3$$

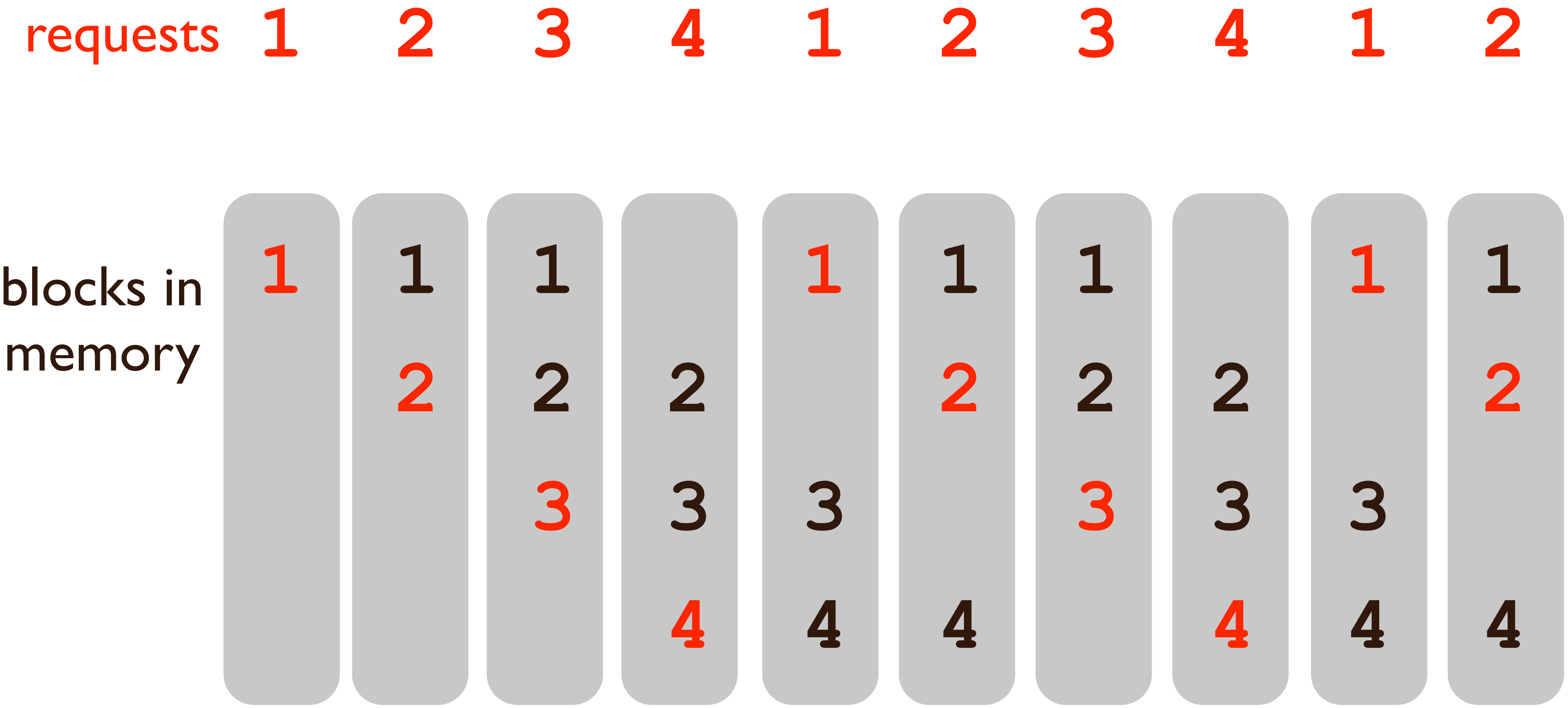
The program accesses 4 different blocks

$$r_j \in \{1, 2, 3, 4\}$$

The request stream is

$$1, 2, 3, 4, 1, 2, 3, 4, \cdots$$

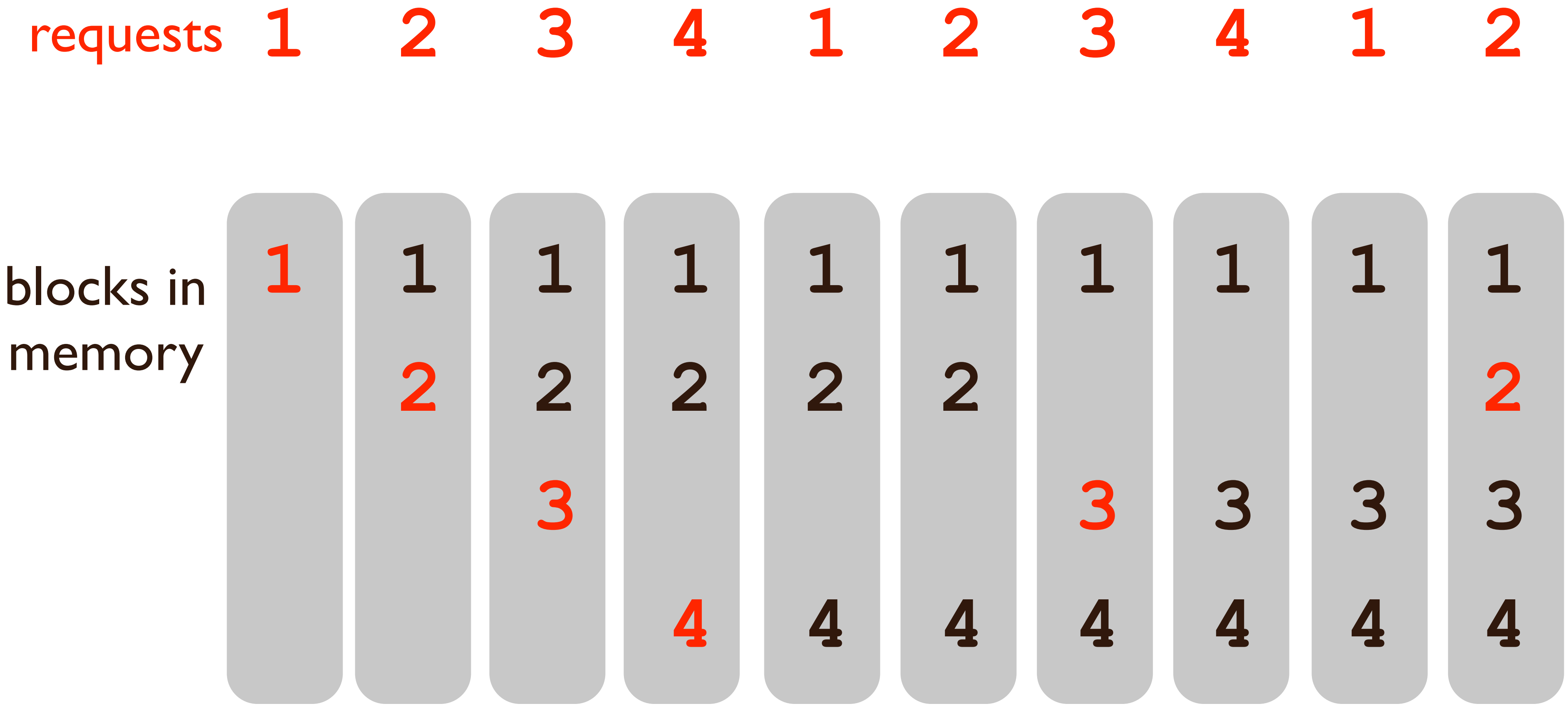
LRU is no better than k-competitive



requests	1	2	3	4	1	2	3	4	1	2
blocks in memory	1	1	1		1	1	1		1	1
		2	2	2		2	2	2		2
			3	3	3		3	3	3	
				4	4	4		4	4	4

There's a block transfer at every step because LRU ejects the block that's requested in the next step.

LRU is no better than k-competitive



requests	1	2	3	4	1	2	3	4	1	2
blocks in memory	1	1	1	1	1	1	1	1	1	1
		2	2	2	2	2				2
			3				3	3	3	3
				4	4	4	4	4	4	4

LFD (longest forward distance) has a block transfer every k=3 steps.

LRU is k-competitive [Sleator, Tarjan 85]

In fact, LRU is *k=M/B*-competitive.

- I.e., LRU has *k=M/B* times more transfers than OPT.
- A depressing result because *k* is huge so *k* · OPT is nothing to write home about.

LFU and FIFO are also *k*-competitive.

- This is a depressing result because FIFO is empirically worse than LRU, and this isn't captured in the math.

On the other hand, the LRU bad example is fragile

requests	1	2	3	4	1	2	3	4	1	2
blocks in memory	1	1	1		1	1	1		1	1
		2	2	2		2	2	2		2
			3	3	3		3	3	3	
				4	4	4		4	4	4

If k=M/B=4, not 3, then both LRU and OPT do well.
If k=M/B=2, not 3, then neither LRU nor OPT does well.

LRU is 2-competitive with more memory [Sleator, Tarjan 85]

LRU is at most twice as bad as OPT, when LRU has twice the memory.

$$\mathrm{LRU}_{|\mathrm{cache}|=k}(R) \leq 2\,\mathrm{OPT}_{|\mathrm{cache}|=k/2}(R)$$

In general, LRU is nearly as good as OPT when LRU has a little more memory than OPT.

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LRU has more memory, but OPT=LFD can see the future.

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$$\mathrm{LRU}_{|\mathrm{cache}|=\underset{\uparrow}{k}}(R) \leq 2\,\mathrm{OPT}_{|\mathrm{cache}|=\underset{\uparrow}{k}/2}(R)$$

LRU has more memory, but OPT=LFD can see the future.

In general, LRU is nearly as good as OPT when LRU has a little more memory than OPT.

(These bounds don't apply to FIFO, distinguishing LRU from FIFO).

LRU Performance Proof

Divide LRU into phases, each with k faults.

$$\underbrace{r_1, r_2, \ldots, r_i,}\ \underbrace{r_{i+1}, \ldots, r_j,}\ \underbrace{r_{j+1}, \ldots, r_\ell,}\ \underbrace{r_{\ell+1}, \ldots}$$

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$$\underbrace{r_1, r_2, \ldots, r_i}, \underbrace{r_{i+1}, \ldots, r_j}, \underbrace{r_{j+1}, \ldots, r_\ell}, \underbrace{r_{\ell+1}, \ldots}$$

OPT[*k*] must have ≥ 1 fault in each phase.

- Case analysis proof.
- LRU is k-competitive.

LRU Performance Proof

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$$\underbrace{r_1, r_2, \ldots, r_i}_{}, \underbrace{r_{i+1}, \ldots, r_j}_{}, \underbrace{r_{j+1}, \ldots, r_\ell}_{}, \underbrace{r_{\ell+1}, \ldots}_{}$$

OPT[*k*] must have ≥ 1 fault in each phase.

- Case analysis proof.
- LRU is k-competitive.

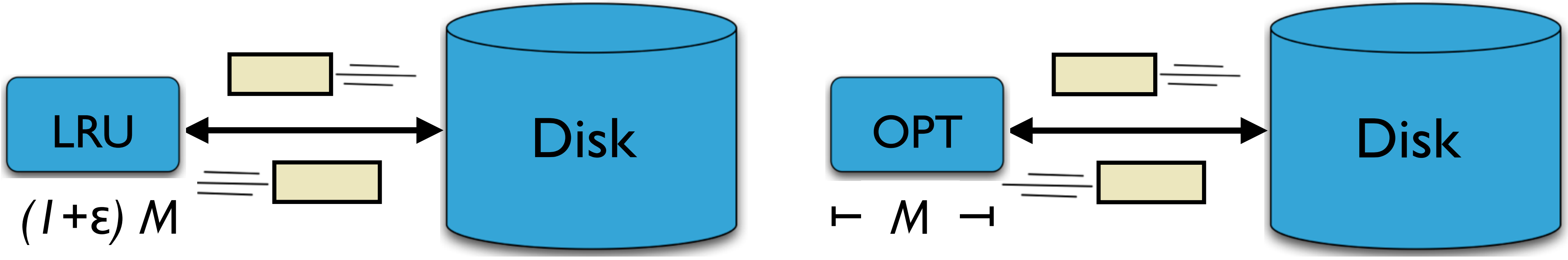
OPT[*k*/2] must have ≥ k/2 faults in each phase.

- Main idea: each phase must touch k different pages.
- LRU is 2-competitive.

Under the hood of cache-oblivious analysis

Moral: with cache-oblivious analysis, we can analyze based on a memory system with optimal, omniscient replacement.

- Technically, an optimal cache-oblivious algorithm is asymptotically optimal versus any algorithm on a memory system that is slightly smaller.
- Empirically, this is just a technicality.



This is almost as good or better... ... than this.

Ramifications for New Cache-Replacement Policies

Moral: There's not much performance on the table for new cache-replacement policies.

- Bad instances for LRU versus LFD are fragile and very sensitive to $k=M/B$.

There are still research questions:

- What if blocks have different sizes [Irani 02][Young 02]?
- There's a write-back cost? (Complexity unknown.)
- LRU may be too costly to implement (clock algorithm).

Data Structures and Algorithms for Big Data

Module 5: What to Index

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MIT & Tokutek

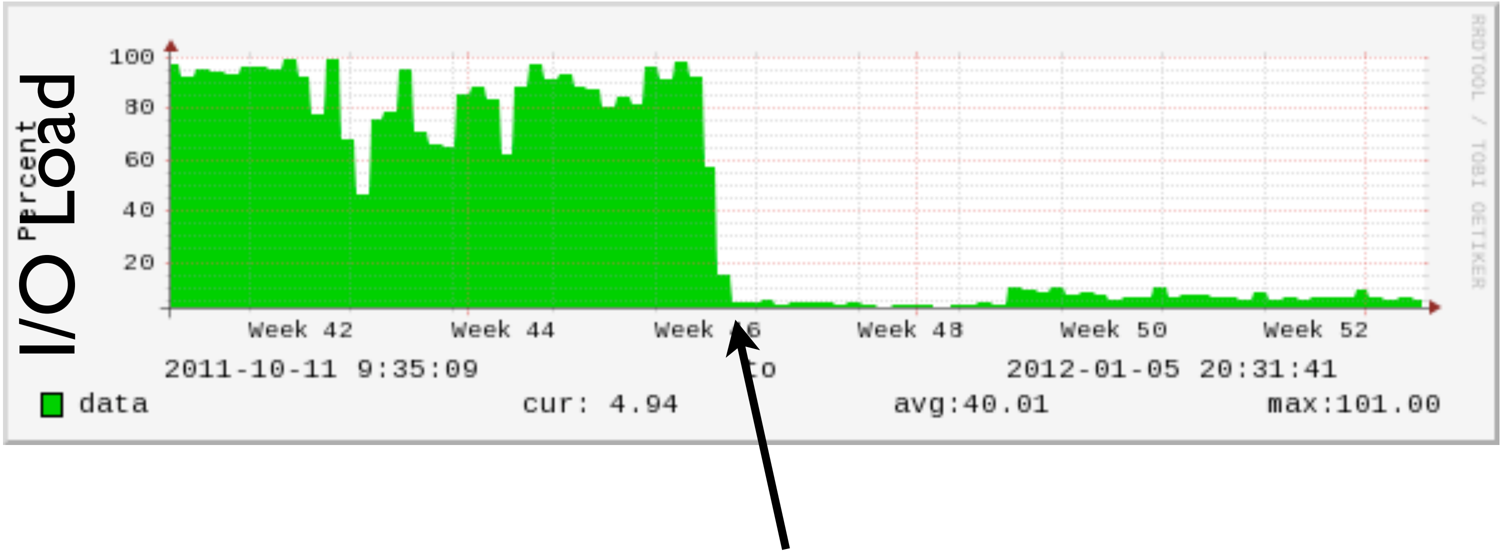
Story of this module

This module explores indexing.

Traditionally, (with B-trees), indexing speeds queries, but cripples insert.

But now we know that maintaining indexes is cheap. So what should you index?

An Indexing Testimonial



Add selective indexes.

This is a graph from a real user, who added some indexes, and reduced the I/O load on their server. (They couldn’t maintain the indexes with B-trees.)

What is an Index?

To understand what to index, we need to get on the same page for what an index is.

Row, Index, and Table

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

Row

- Key,value pair
- key = a, value = b,c

Index

- Ordering of rows by key (dictionary)
- Used to make queries fast

Table

- Set of indexes

```
create table foo (a int, b int, c int,
primary key(a));
```

An index is a dictionary

Dictionary API: maintain a set S subject to

- insert(x): $S \leftarrow S \cup \{x\}$
- delete(x): $S \leftarrow S - \{x\}$
- search(x): is $x \in S$?
- successor(x): return min $y > x$ s.t. $y \in S$
- predecessor(y): return max $y < x$ s.t. $y \in S$

We assume that these operations perform as well as a B-tree. For example, the successor operation usually doesn't require an I/O.

A table is a set of indexes

A table is a set of indexes with operations:

- Add index: `add key(f₁,f₂,...);`
- Drop index: `drop key(f₁,f₂,...);`
- Add column: adds a field to primary key value.
- Remove column: removes a field and drops all indexes where field is part of key.
- Change field type
- ...

Subject to index correctness constraints.

We want table operations to be fast too.

Next: how to use indexes to improve queries.

Indexes provide query performance

1. Indexes can reduce the amount of retrieved data.

- Less bandwidth, less processing, ...

2. Indexes can improve locality.

- Not all data access cost is the same
- Sequential access is MUCH faster than random access

3. Indexes can presort data.

- GROUP BY and ORDER BY queries do post-retrieval work
- Indexing can help get rid of this work

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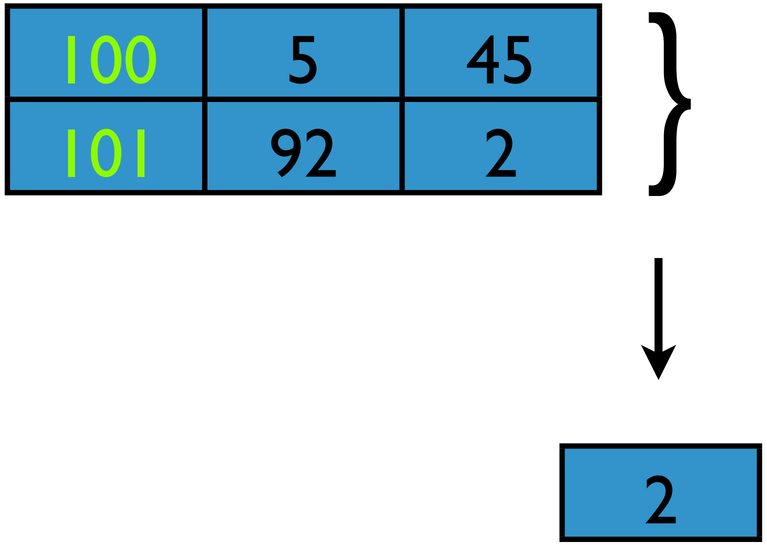
An index can select needed rows

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

```
count (*) where a<120;
```

An index can select needed rows

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45



100	5	45
101	92	2

2

```
count (*) where a<120;
```

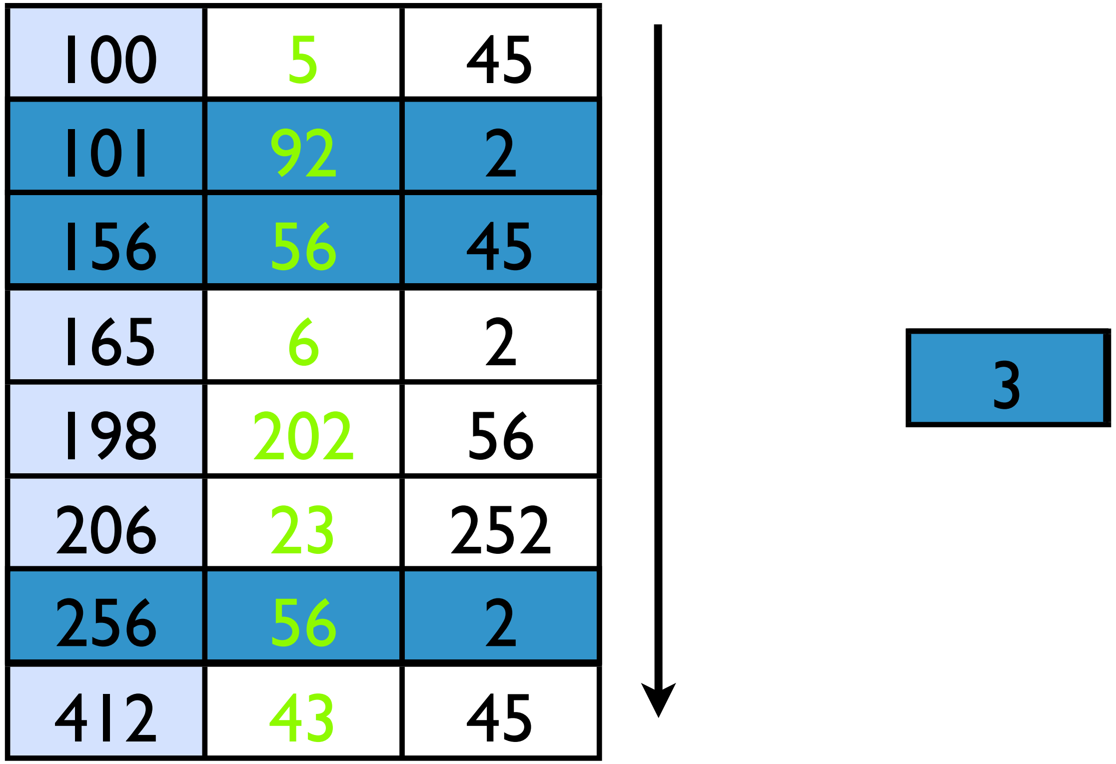
No good index means slow table scans

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

```
count (*) where b>50 and b<100;
```

No good index means slow table scans

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45



100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

```
count (*) where b>50 and b<100;
```

You can add an index

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

b	a
5	100
6	165
23	206
43	412
56	156
56	256
92	101
202	198

```
alter table foo add key(b);
```

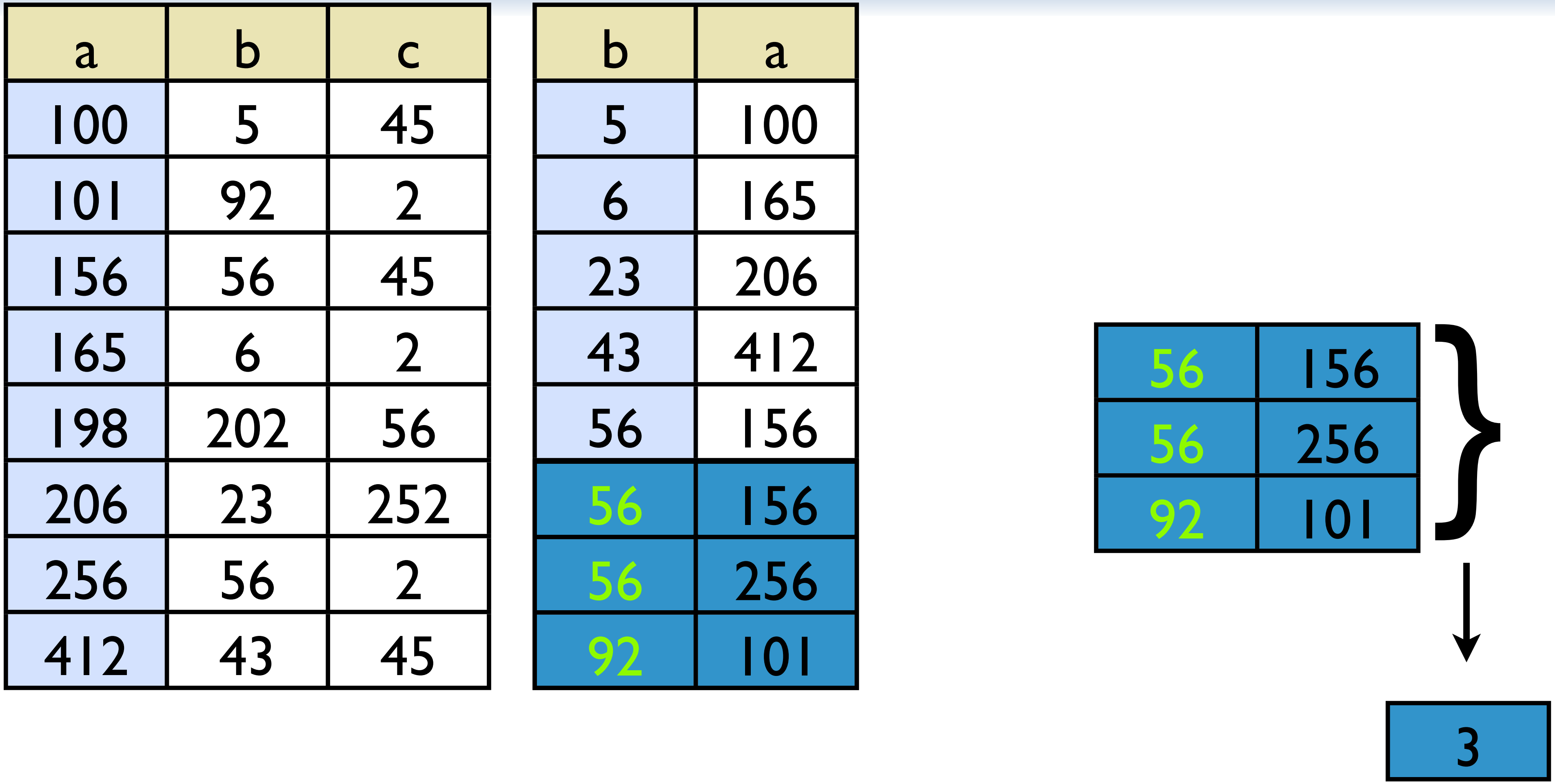
A selective index speeds up queries

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

b	a
5	100
6	165
23	206
43	412
56	156
56	256
92	101
202	198

```
count (*) where b>50 and b<100;
```

A selective index speeds up queries



a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

b	a
5	100
6	165
23	206
43	412
56	156
56	156
56	256
92	101

56	156
56	256
92	101

3

```
count (*) where b>50 and b<100;
```

Selective indexes can still be slow

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

b	a
5	100
6	165
23	206
43	412
56	156
56	256
92	101
202	198

```
sum(c) where b>50;
```

Selective indexes can still be slow

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

b	a
5	100
6	165
23	206
43	412
56	156
56	256
92	101
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↓

Selecting
on b: fast

```
sum(c) where b>50;
```

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a	b	c
100	5	45
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156	56	45
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92	101
202	198

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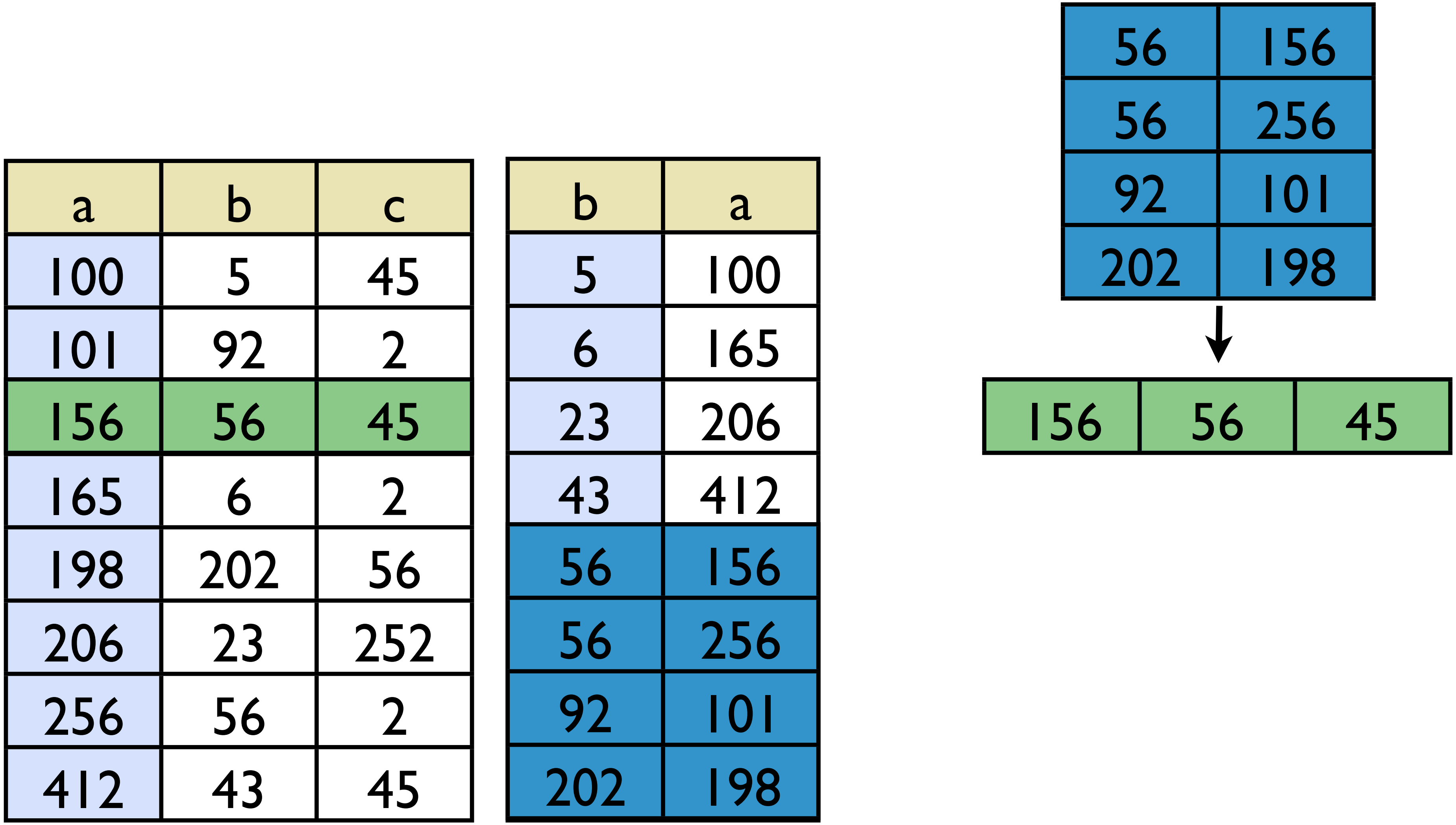
Selecting on b: fast

Fetching info for summing c: slow

```
sum(c) where b>50;
```

Selective indexes can still be slow



a	b	c
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Selecting on b: fast

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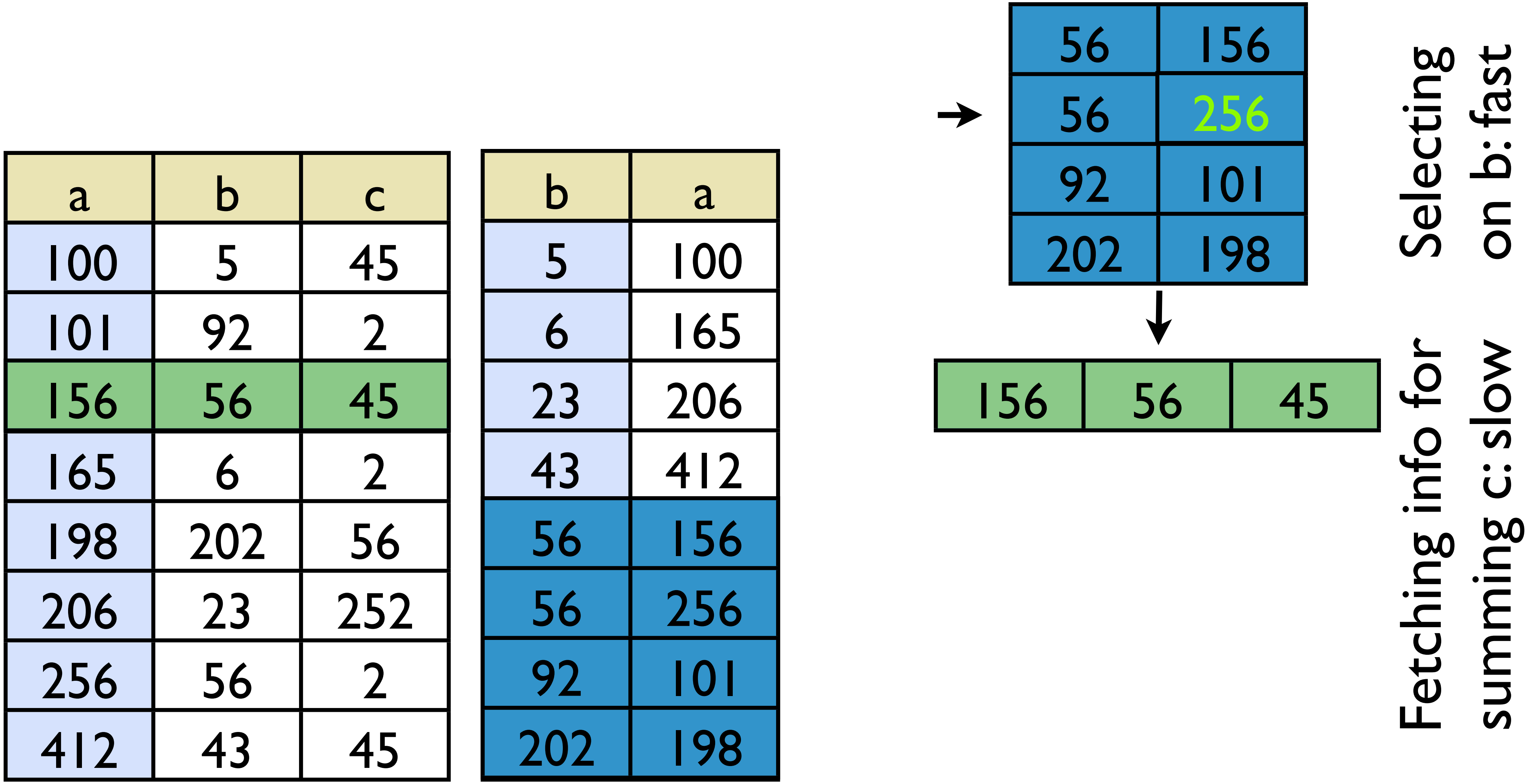
Selective indexes can still be slow



a	b	c
100	5	45
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Selecting on b: fast

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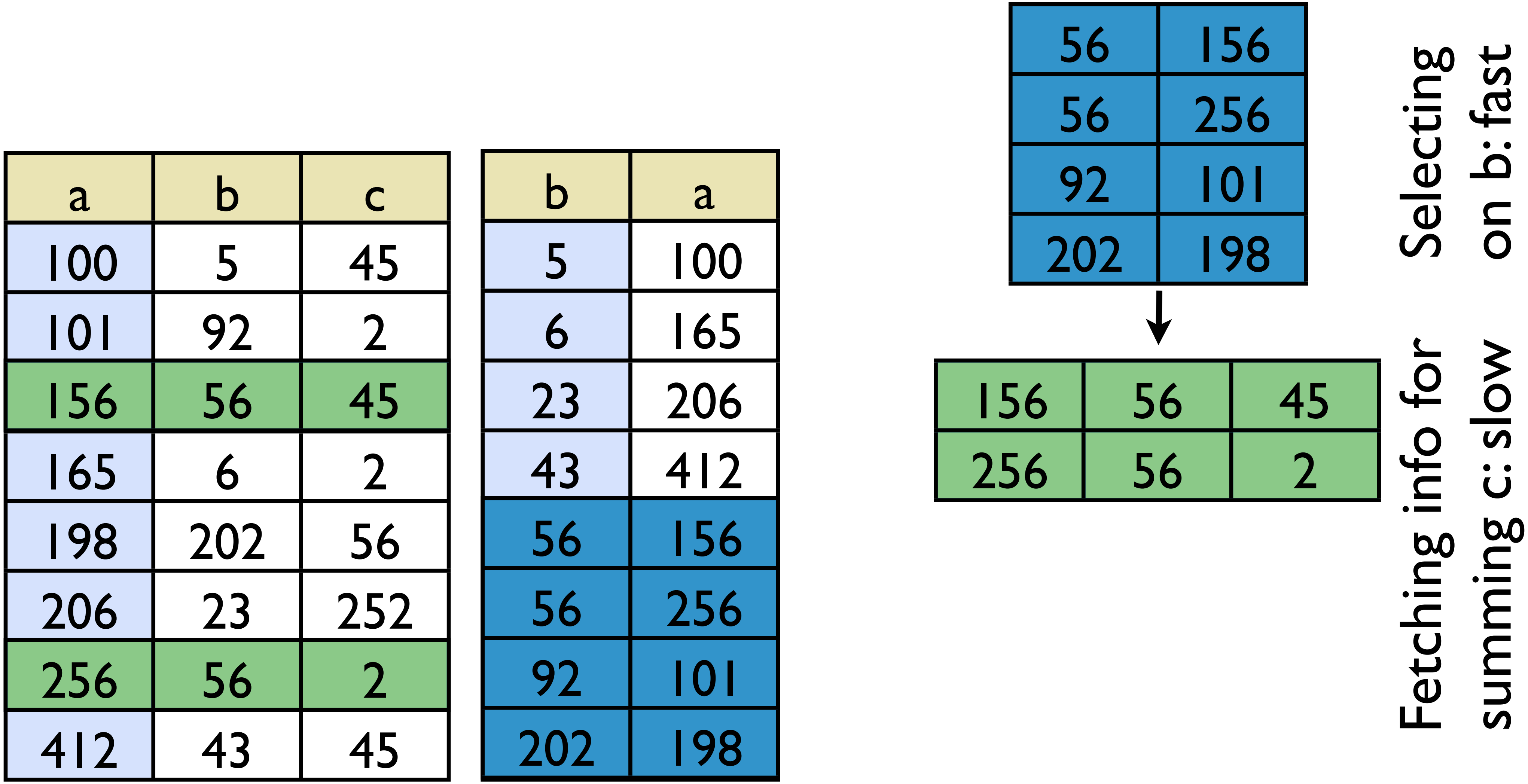
Selective indexes can still be slow



a	b	c
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Selecting on b: fast

156	56	45
256	56	2

Fetching info for summing c: slow

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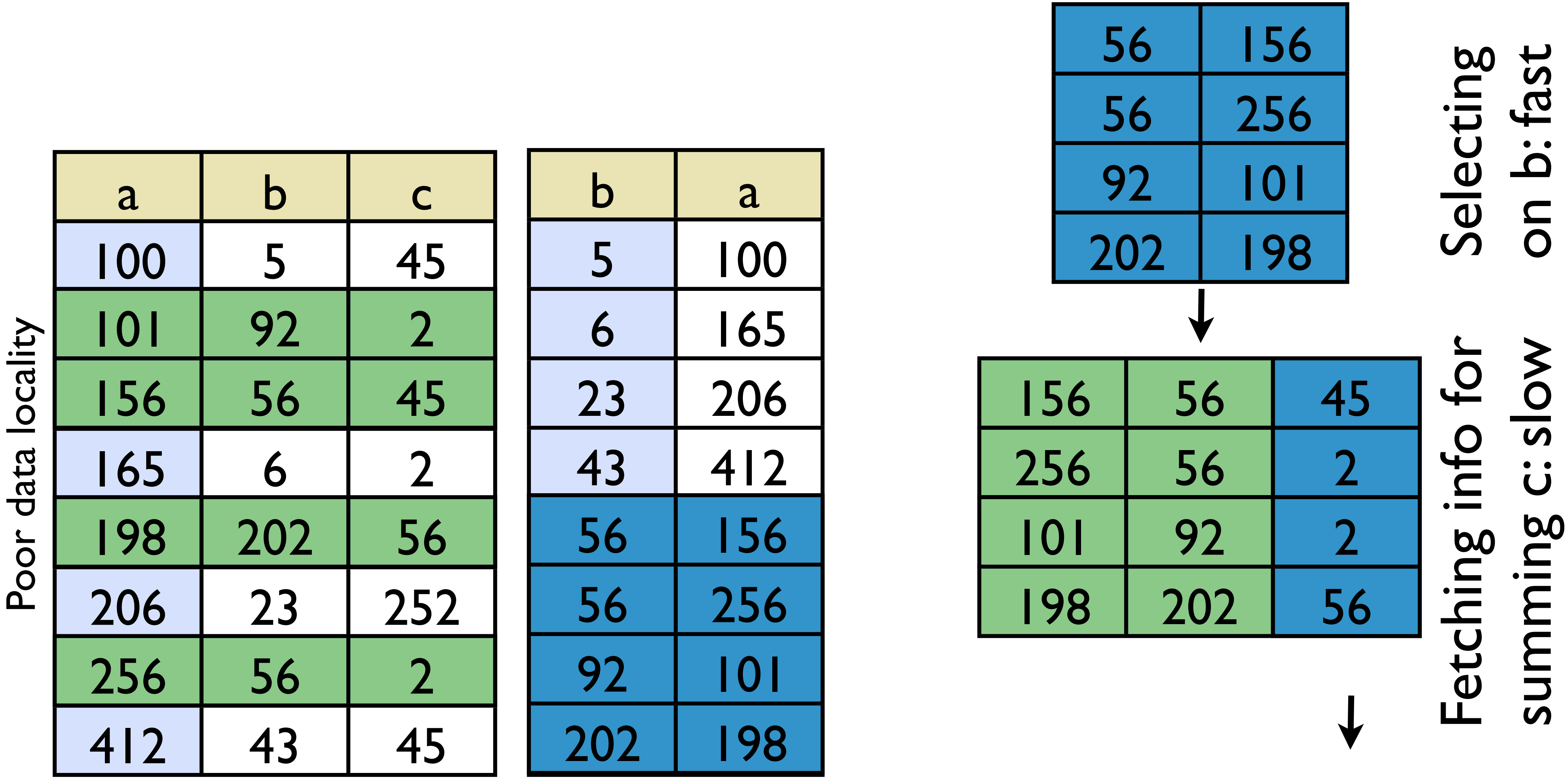
Selective indexes can still be slow



Poor data locality

a	b	c
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5	100
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43	412
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56	256
92	101
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56	156
56	256
92	101
202	198

Selecting on b: fast

156	56	45
256	56	2
101	92	2
198	202	56

Fetching info for summing c: slow

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sum(c) where b>50;
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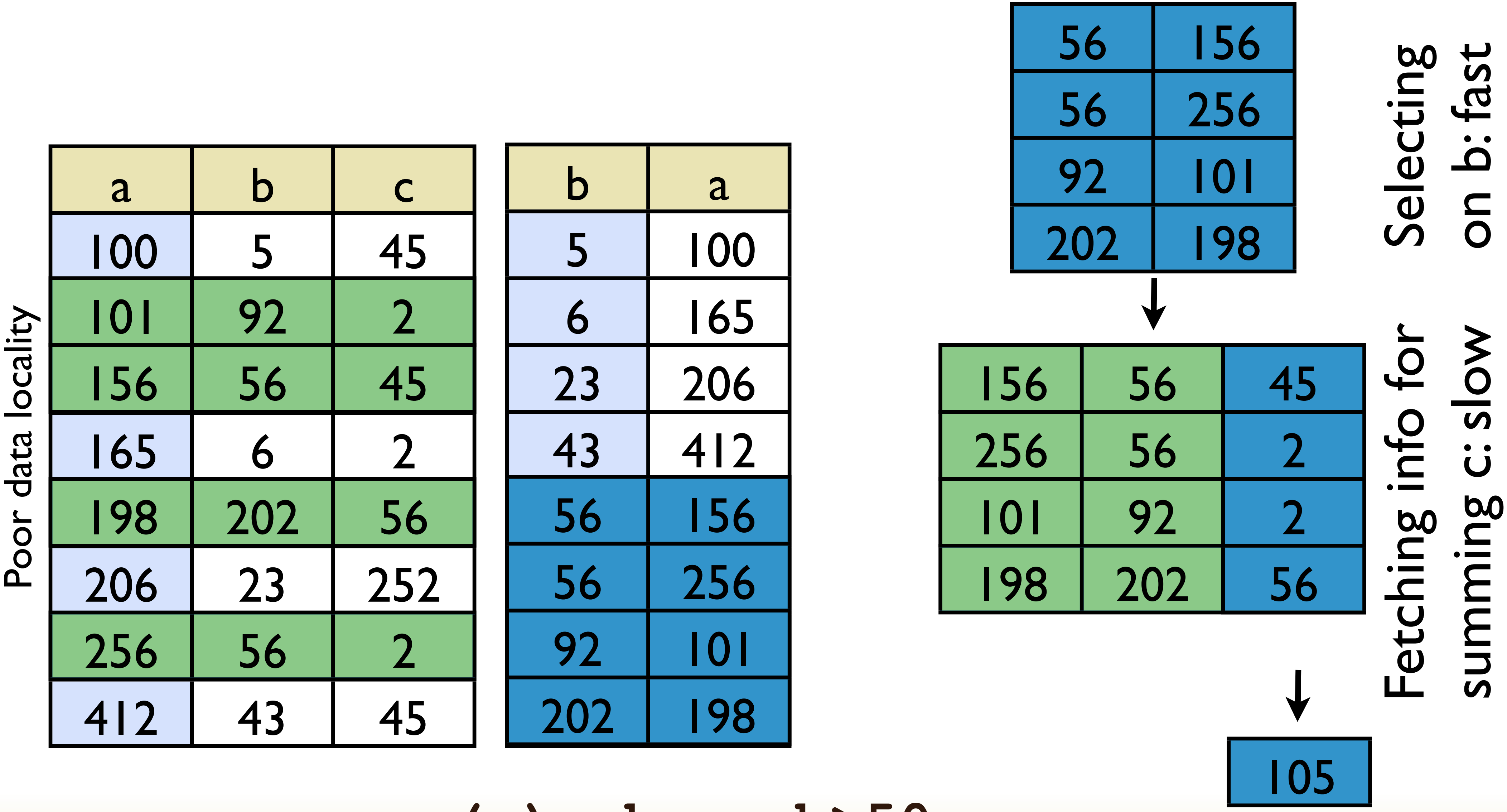
Selective indexes can still be slow



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56	156
56	256
92	101
202	198

Selecting on b: fast

↓

156	56	45
256	56	2
101	92	2
198	202	56

Fetching info for summing c: slow

↓

105

```
sum(c) where b>50;
```

Indexes provide query performance

1. Indexes can reduce the amount of retrieved data.

- Less bandwidth, less processing, ...

2. Indexes can improve locality.

- Not all data access cost is the same
- Sequential access is MUCH faster than random access

3. Indexes can presort data.

- GROUP BY and ORDER BY queries do post-retrieval work
- Indexing can help get rid of this work

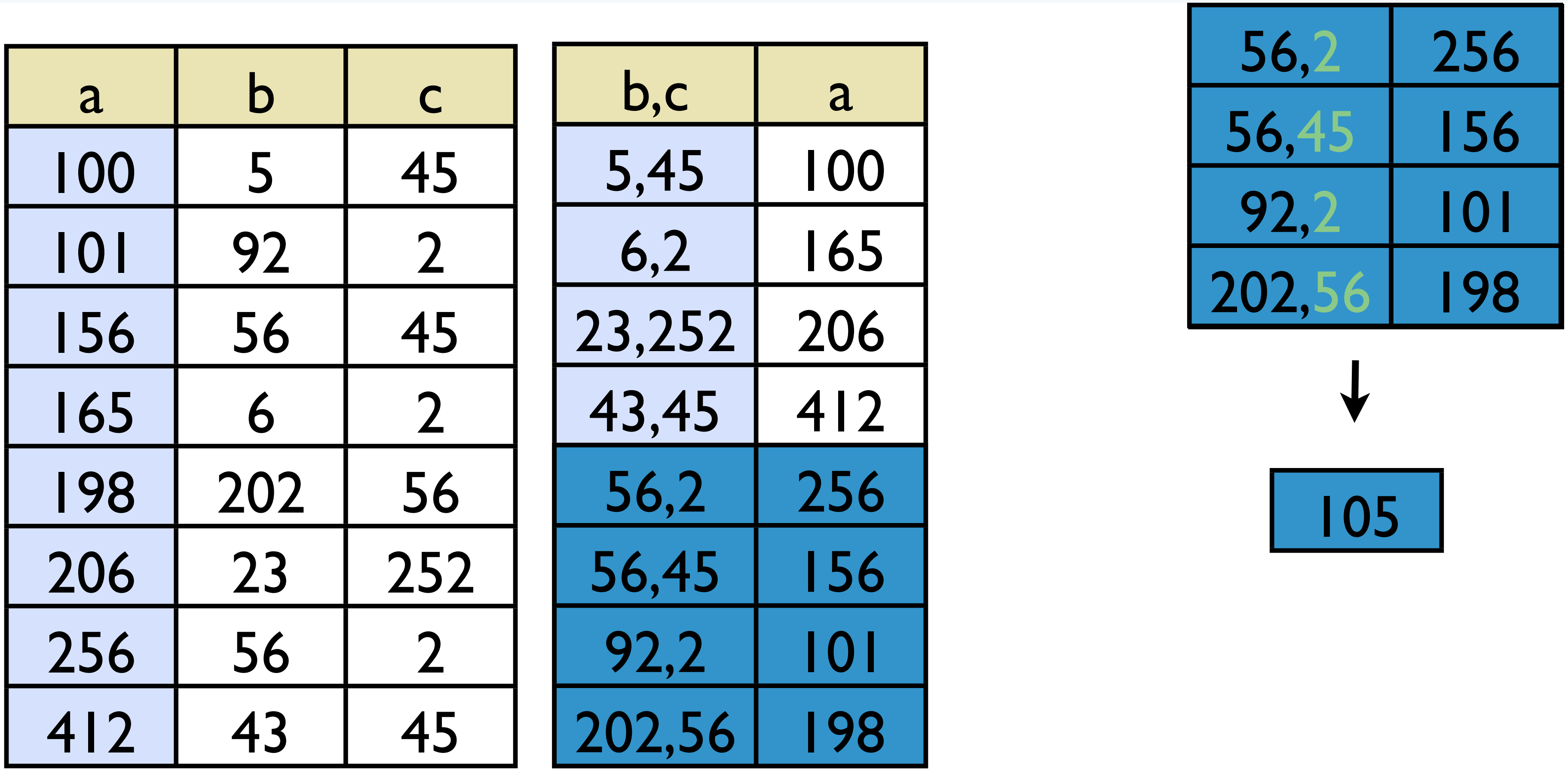
Covering indexes speed up queries

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

b,c	a
5,45	100
6,2	165
23,252	206
43,45	412
56,2	256
56,45	156
92,2	101
202,56	198

```
alter table foo add key(b,c);
sum(c) where b>50;
```

Covering indexes speed up queries



a	b	c
100	5	45
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206	23	252
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412	43	45

b,c	a
5,45	100
6,2	165
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56,2	256
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↓

105

```
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sum(c) where b>50;
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Indexes provide query performance

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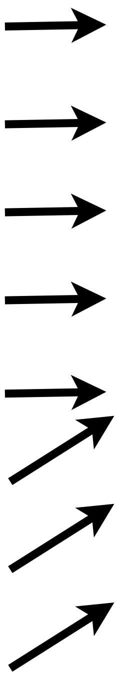
Indexes can avoid post-selection sorts

a	b	c
100	5	45
101	92	2
156	56	45
165	6	2
198	202	56
206	23	252
256	56	2
412	43	45

b,c	a
5,45	100
6,2	165
23,252	206
43,45	412
56,2	256
56,45	156
92,2	101
202,56	198



b	sum(c)
5	45
6	2
23	252
43	45
56	47
92	2
202	56

```
select b, sum(c) group by b;
sum(c) where b>50;
```

Data Structures and Algorithms for Big Data

Module 6: Log Structured Merge Trees

Michael A. Bender
Stony Brook & Tokutek

Bradley C. Kuszmaul
MIT & Tokutek

Log Structured Merge Trees

[O'Neil, Cheng, Gawlick, O'Neil 96]

Log structured merge trees are write-optimized data structures developed in the 90s.

Over the past 5 years, LSM trees have become popular (for good reason).

Accumulo, Bigtable, bLSM, Cassandra, HBase, Hypertable, LevelDB are LSM trees (or borrow ideas).

http://nosql-database.org lists 122 NoSQL databases. Many of them are LSM trees.

Recall Optimal Search-Insert Tradeoff [Brodal, Fagerberg 03]

	insert	**point query**
Optimal tradeoff (function of ε=0...1)	$O\left(\frac{\log_{1+B^\varepsilon} N}{B^{1-\varepsilon}}\right)$	$O\left(\log_{1+B^\varepsilon} N\right)$

LSM trees don't lie on the optimal search-insert tradeoff curve.

But they're not far off.

We'll show how to move them back onto the optimal curve.

Log Structured Merge Tree

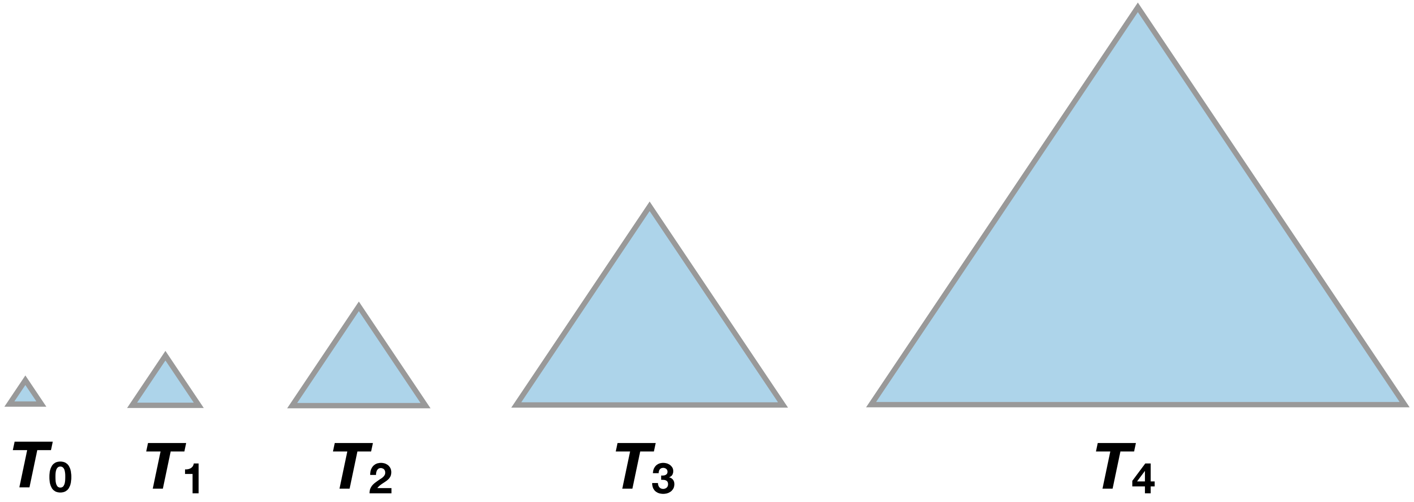
[O'Neil, Cheng, Gawlick, O'Neil 96]

An LSM tree is a cascade of B-trees.

Each tree T_j has a *target size* $|T_j|$.

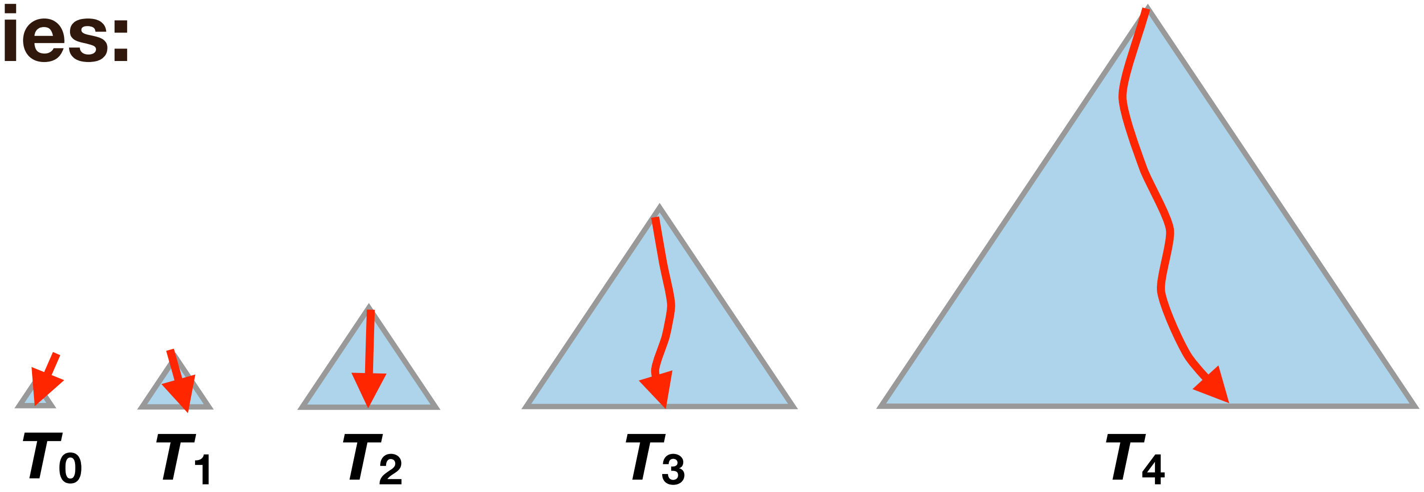
The target sizes are exponentially increasing.

Typically, target size $|T_{j+1}| = 10\ |T_j|$.



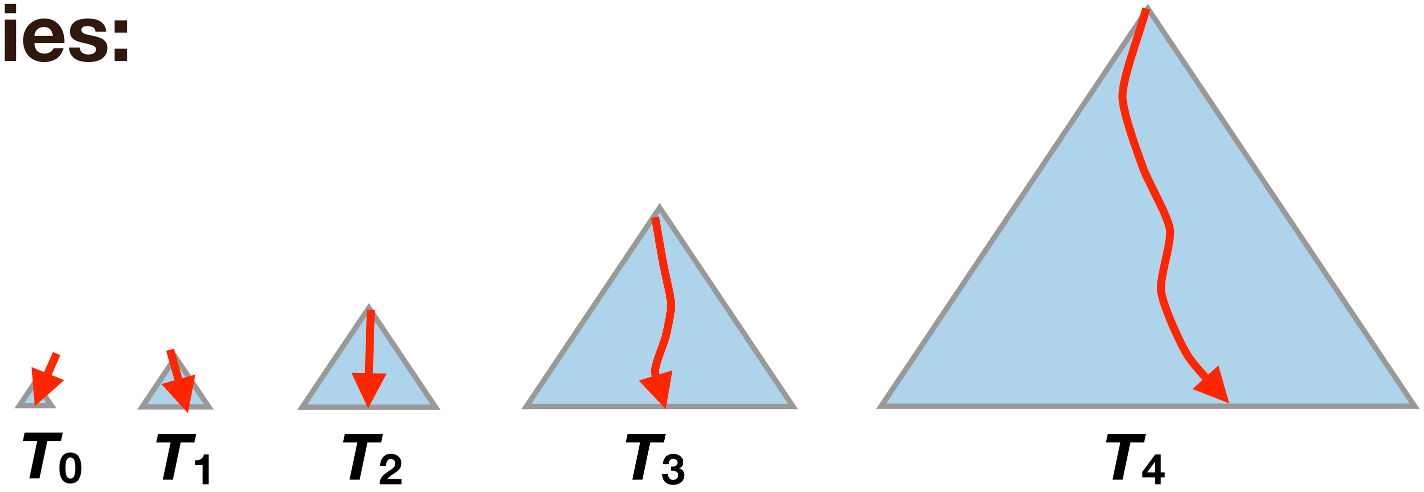
LSM Tree Operations

Point queries:

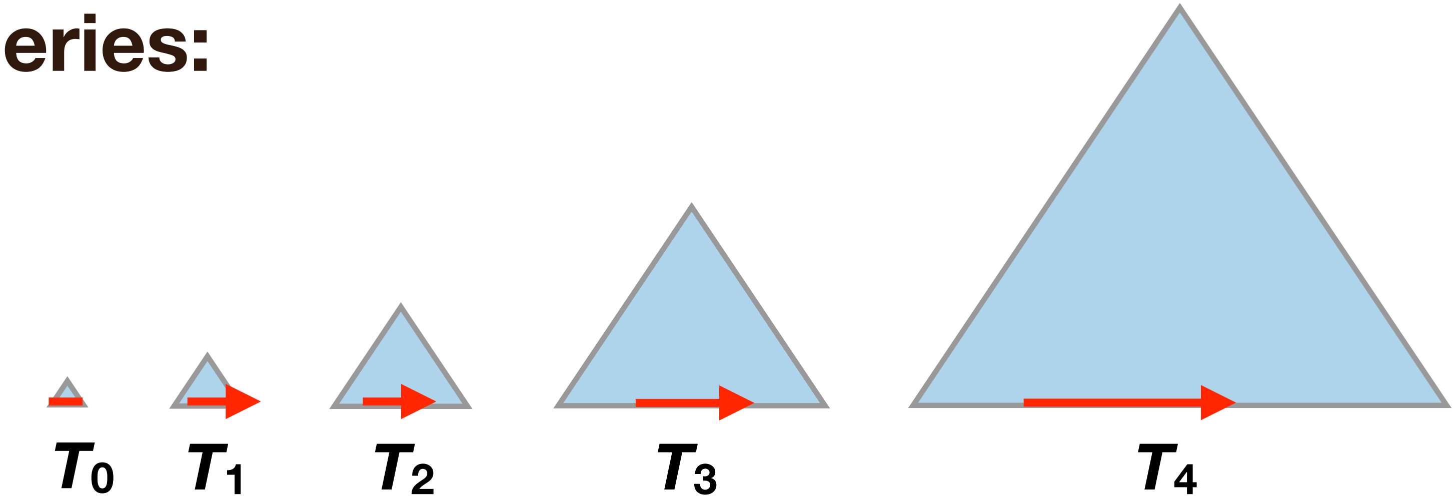


LSM Tree Operations

Point queries:



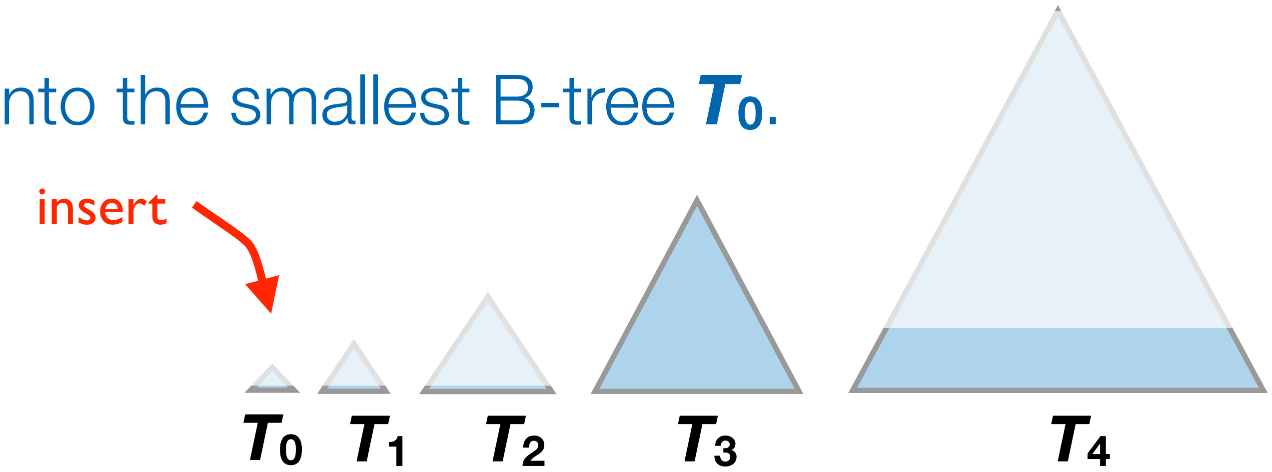
Range queries:



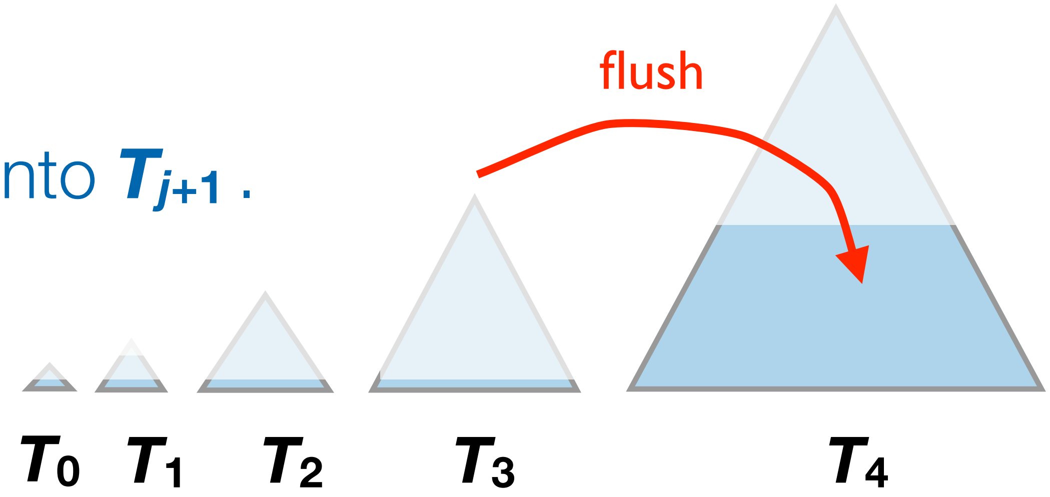
LSM Tree Operations

Insertions:

- Always insert element into the smallest B-tree T_0.



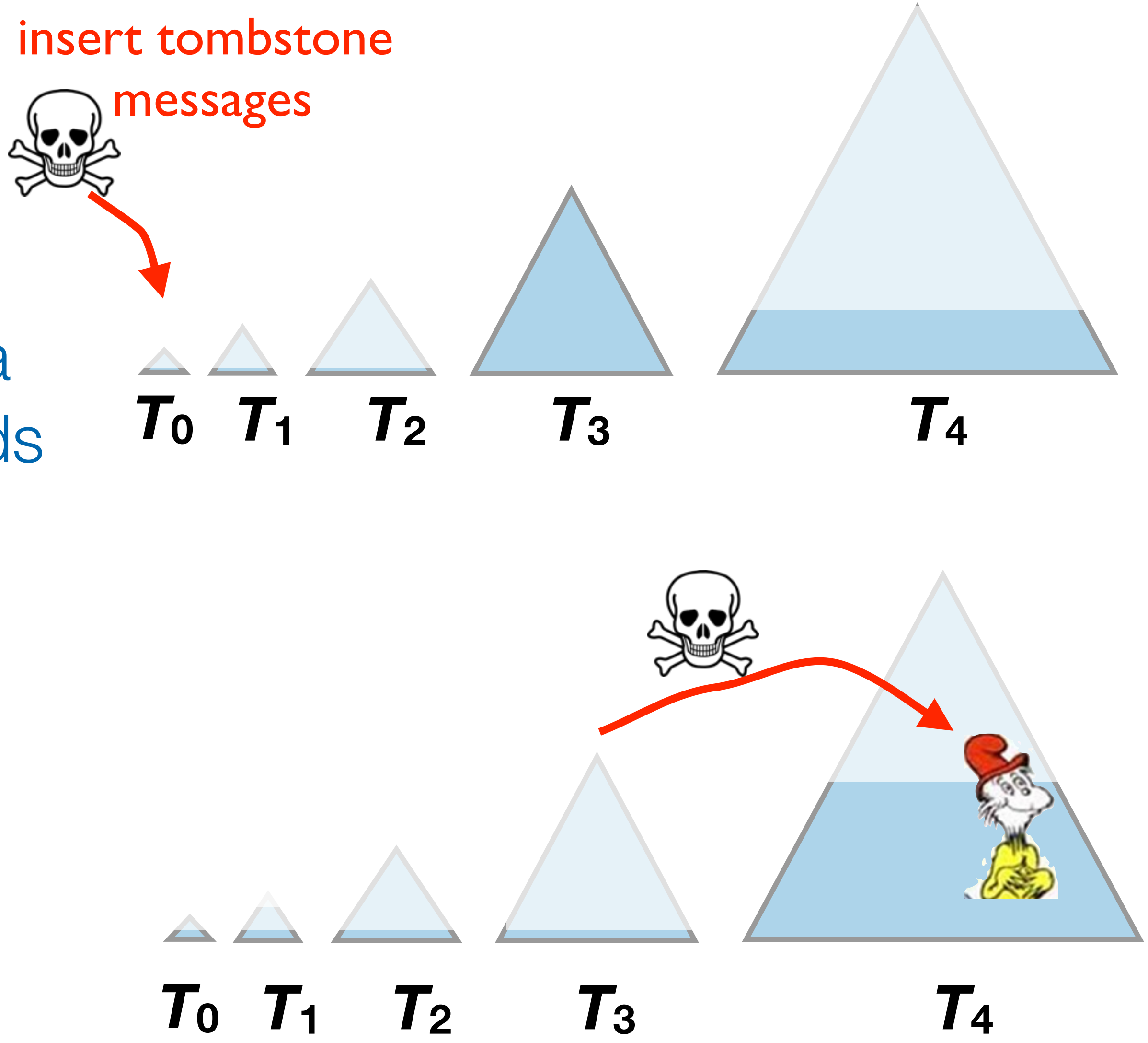
- When a B-tree T_j fills up, flush into T_{j+1} .



LSM Tree Operations

Deletes are like inserts:

- Instead of deleting an element directly, insert tombstones.
- A tombstone knocks out a “real” element when it lands in the same tree.

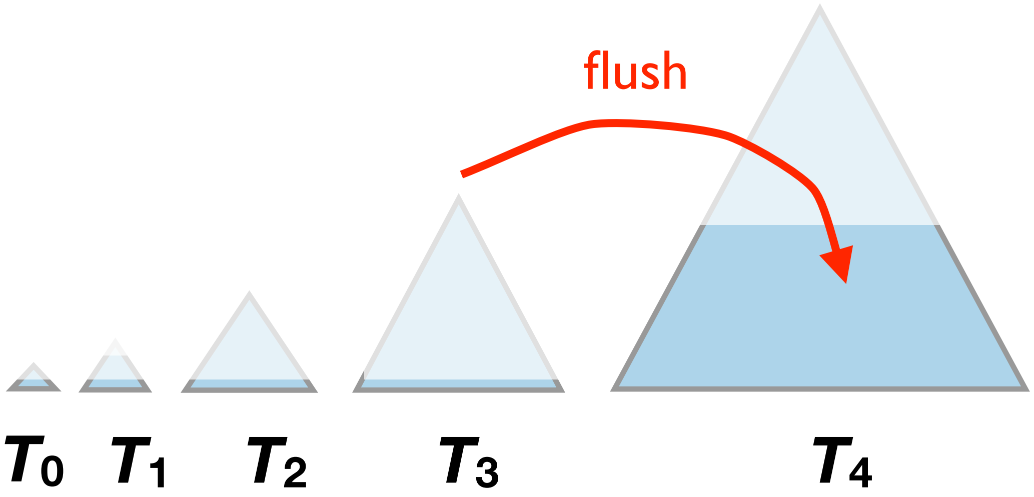


insert tombstone messages

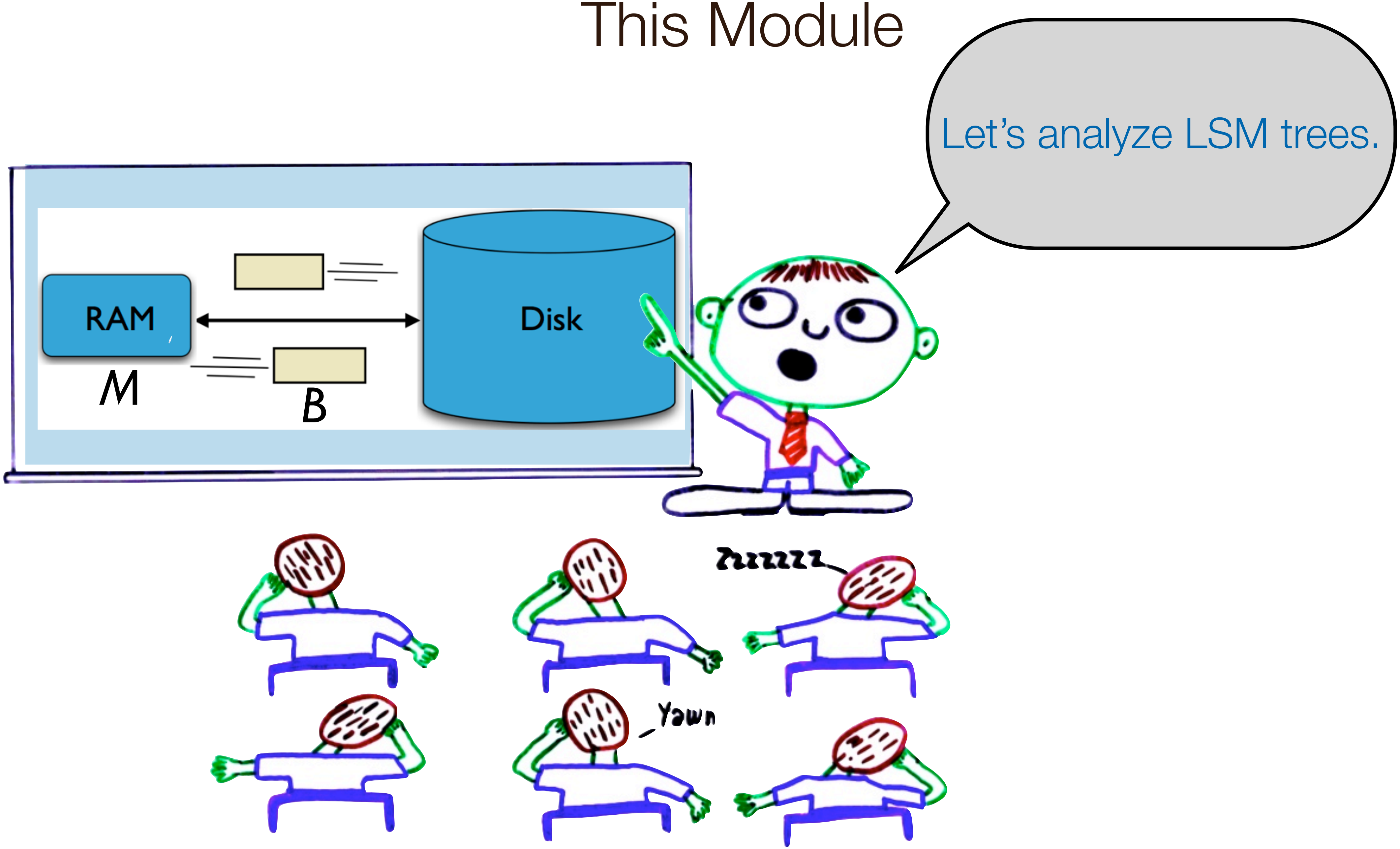
Static-to-Dynamic Transformation

An LSM Tree is an example of a "static-to-dynamic" transformation [Bentley, Saxe '80] .

- An LSM tree can be built out of ***static B-trees.***
- When $\boldsymbol{T}_3$ flushes into $\boldsymbol{T}_4$, $\boldsymbol{T}_4$ is rebuilt from scratch.

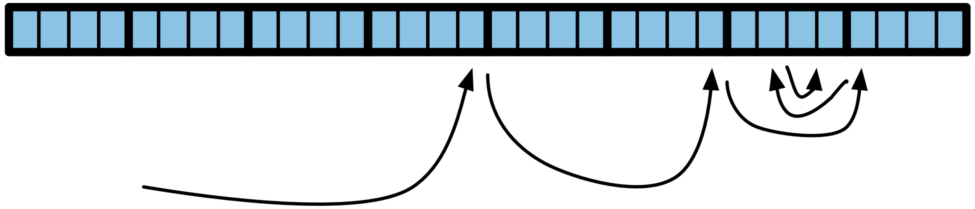


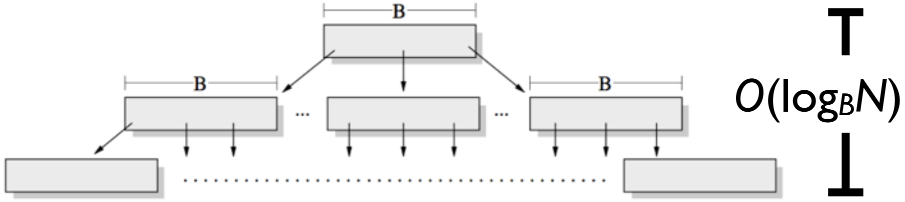
This Module



Recall: Searching in an Array Versus B-tree

Recall the cost of searching in an array versus a B-tree.

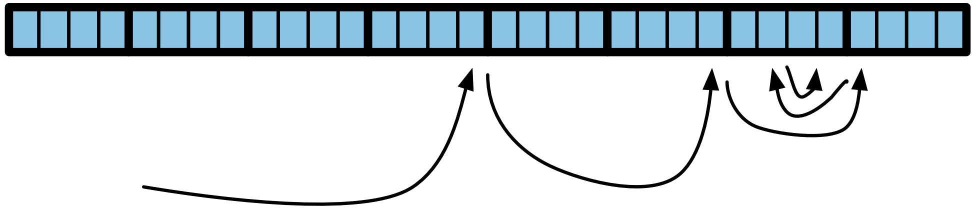


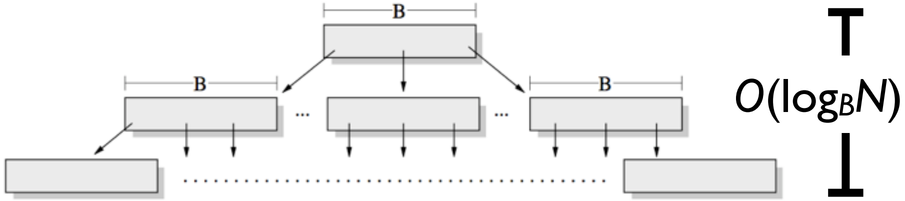


$$O(\log_B N) = O\left(\frac{\log_2 N}{\log_2 B}\right)$$

Recall: Searching in an Array Versus B-tree

Recall the cost of searching in an array versus a B-tree.





$$O\left(\log_2 \frac{N}{B}\right) \approx O(\log_2 N)$$

$$O(\log_B N) = O\left(\frac{\log_2 N}{\log_2 B}\right)$$

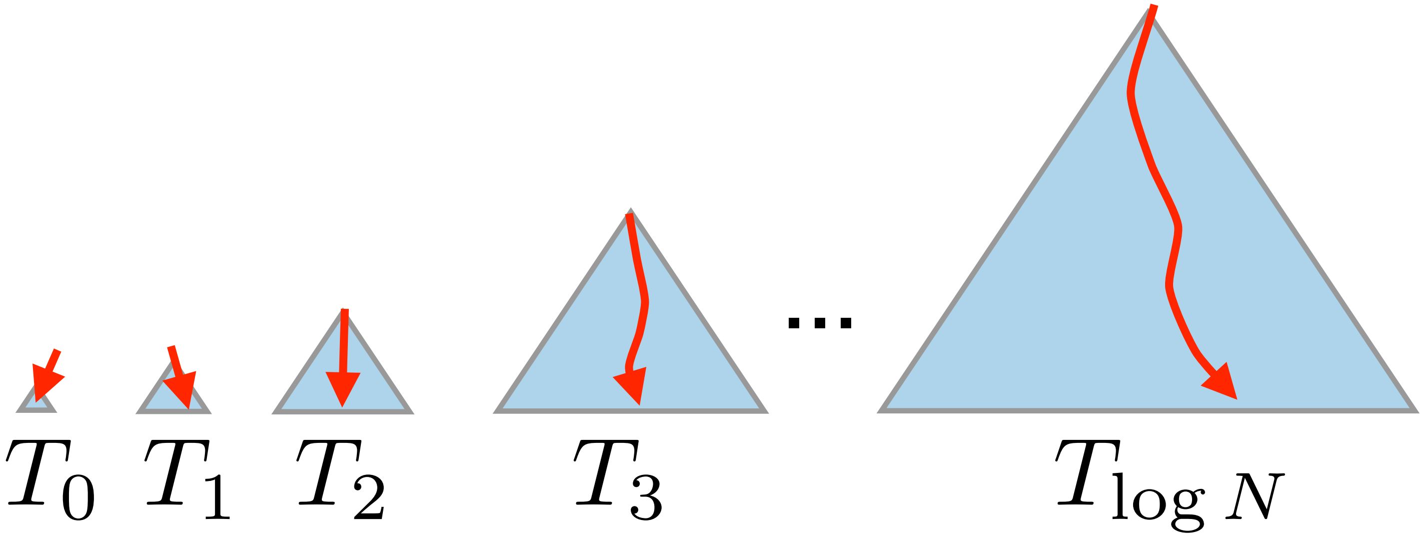
Analysis of point queries

Search cost:

$$\log_B N + \log_B N/2 + \log_B N/4 + \cdots + \log_B B$$

$$= \frac{1}{\log B} (\log N + \log N - 1 + \log N - 2 + \log N - 3 + \cdots + 1)$$

$$= O(\log N \log_B N)$$



Insert Analysis

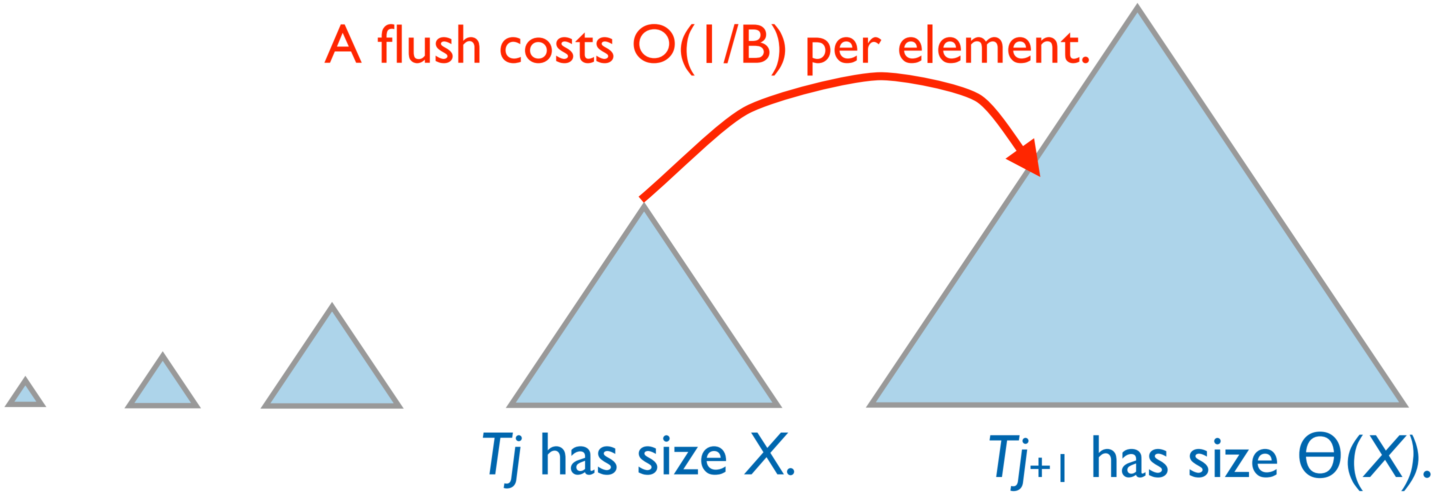
The cost to flush a tree *Tj* of size *X* is O(*X*/*B*).

- Flushing and rebuilding a tree is just a linear scan.

The cost per element to flush *Tj* is O(*1*/*B*).

The # times each element is moved is ≤ log *N*.

The insert cost is O((log *N*)/*B*) amortized memory transfers.



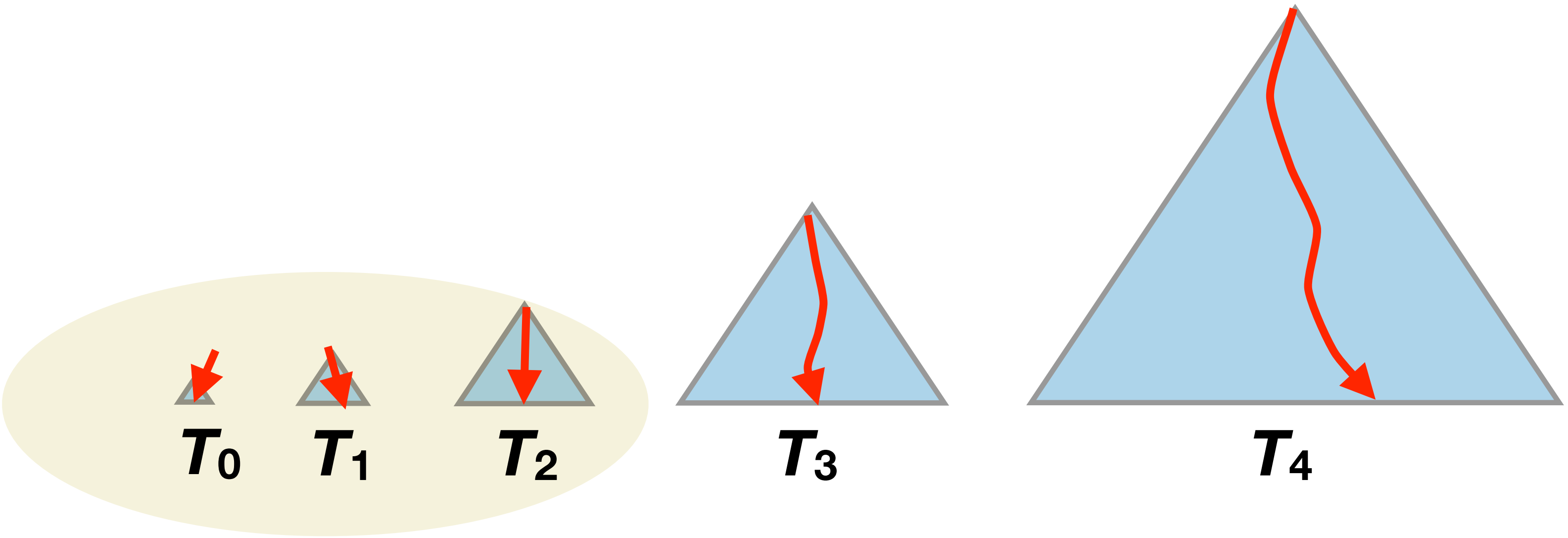
Samples from LSM Tradeoff Curve

	insert	**point query**
tradeoff (function of ε)	$O\left(\frac{\log_{1+B^\varepsilon} N}{B^{1-\varepsilon}}\right)$	$O\left((\log_B N)(\log_{1+B^\varepsilon} N)\right)$
sizes grow by *B* (ε=1)	$O\left(\log_B N\right)$	$O\left((\log_B N)(\log_B N)\right)$
sizes grow by $B^{1/2}$ (ε=1/2)	$O\left(\frac{\log_B N}{\sqrt{B}}\right)$	$O\left((\log_B N)(\log_B N)\right)$
sizes double (ε=0)	$O\left(\frac{\log N}{B}\right)$	$O\left((\log_B N)(\log N)\right)$

How to improve LSM-tree point queries?

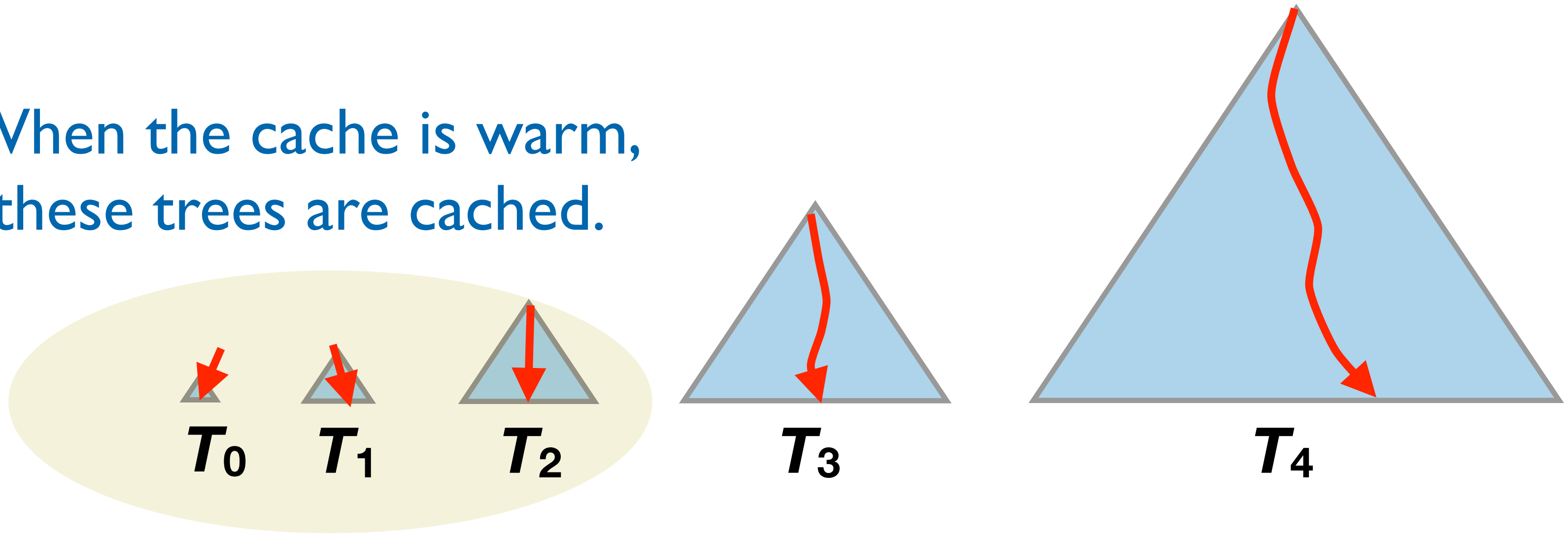
Looking in all those trees is expensive, but can be improved by

- caching,
- Bloom filters, and
- fractional cascading.



Caching in LSM trees

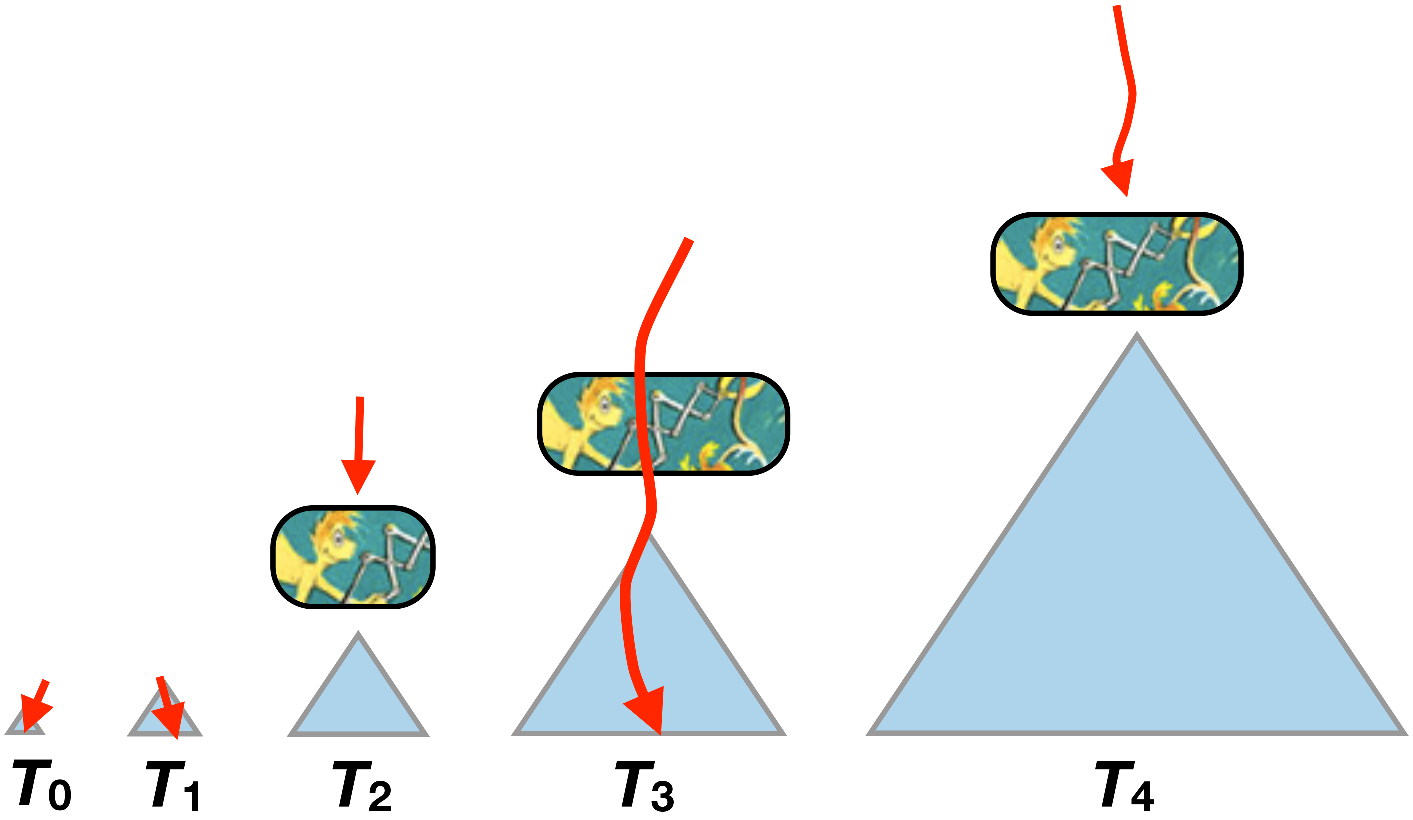
When the cache is warm, small trees are cached.



Bloom filters in LSM trees

Bloom filters can avoid point queries for elements that are not in a particular B-tree.

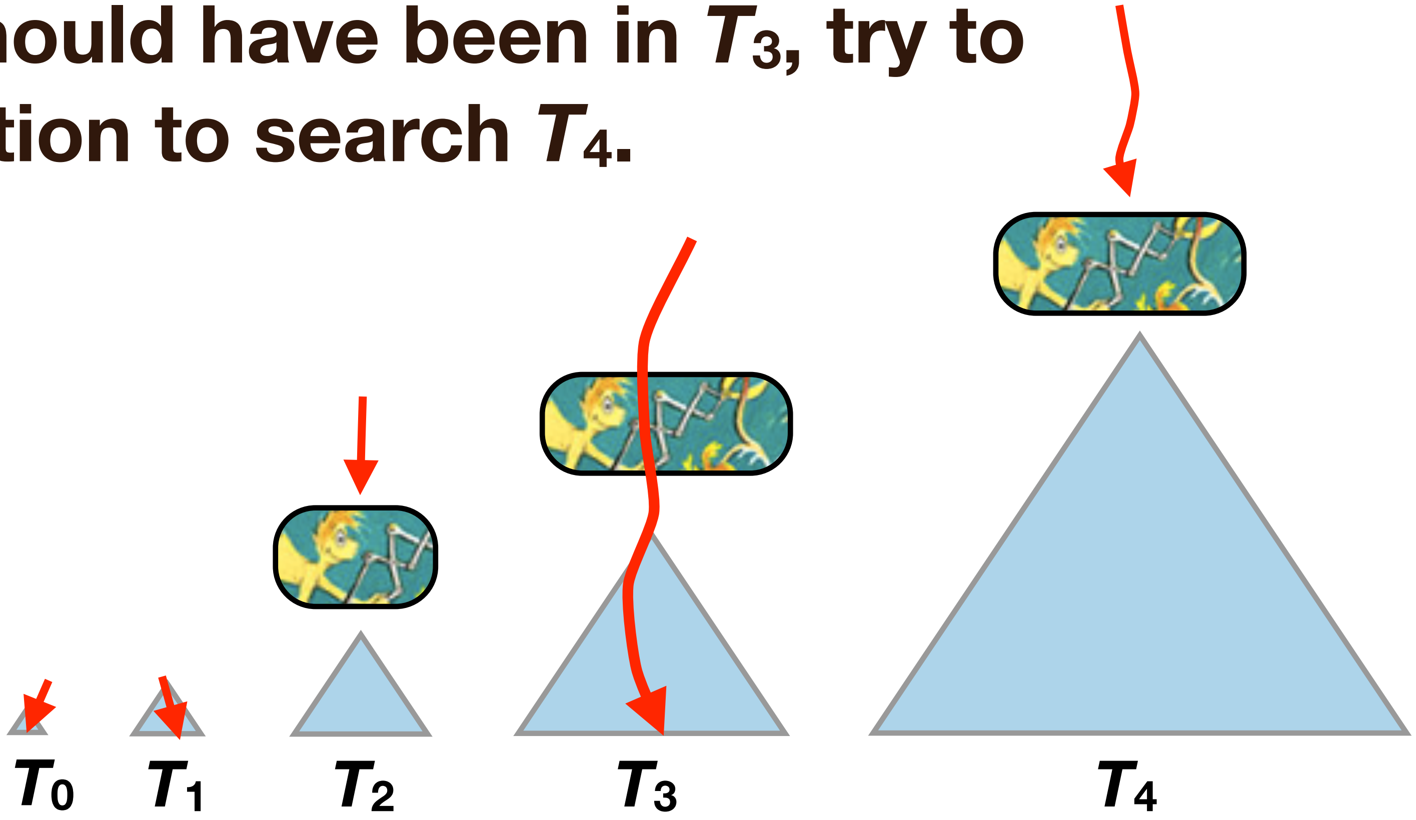
We'll see how Bloom filters work later.



Fractional cascading reduces the cost in each tree

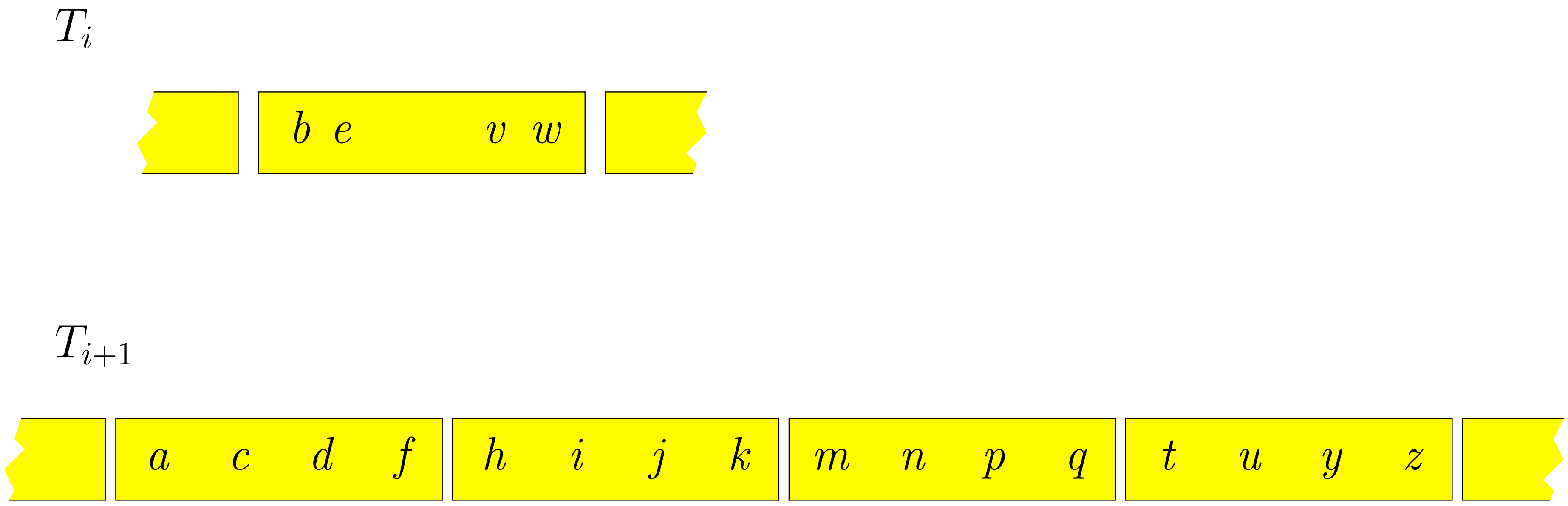
Instead of avoiding searches in trees, we can use a technique called *fractional cascading* to reduce the cost of searching each B-tree to $O(1)$.

Idea: We're looking for a key, and we already know where it should have been in T_3, try to use that information to search T_4.



Searching one tree helps in the next

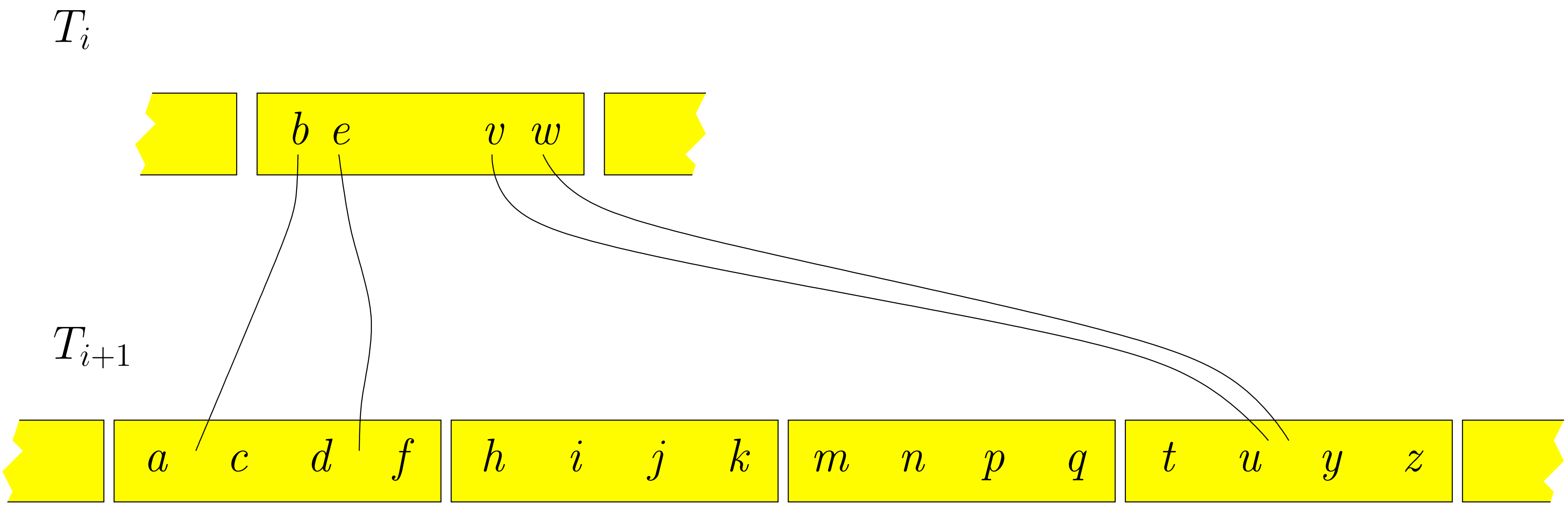
Looking up *c*, in *Ti* we know it’s between *b*, and *e*.



Showing only the bottom level of each B-tree.

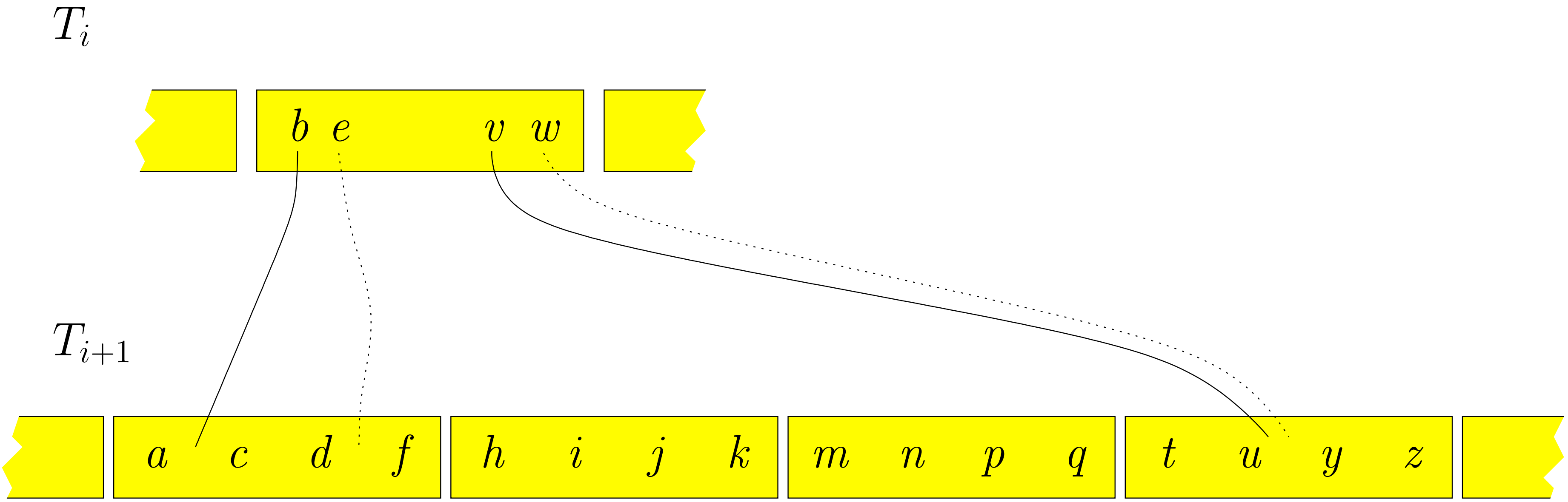
Forwarding pointers

If we add *forwarding pointers* to the first tree, we can jump straight to the node in the second tree, to find *c*.



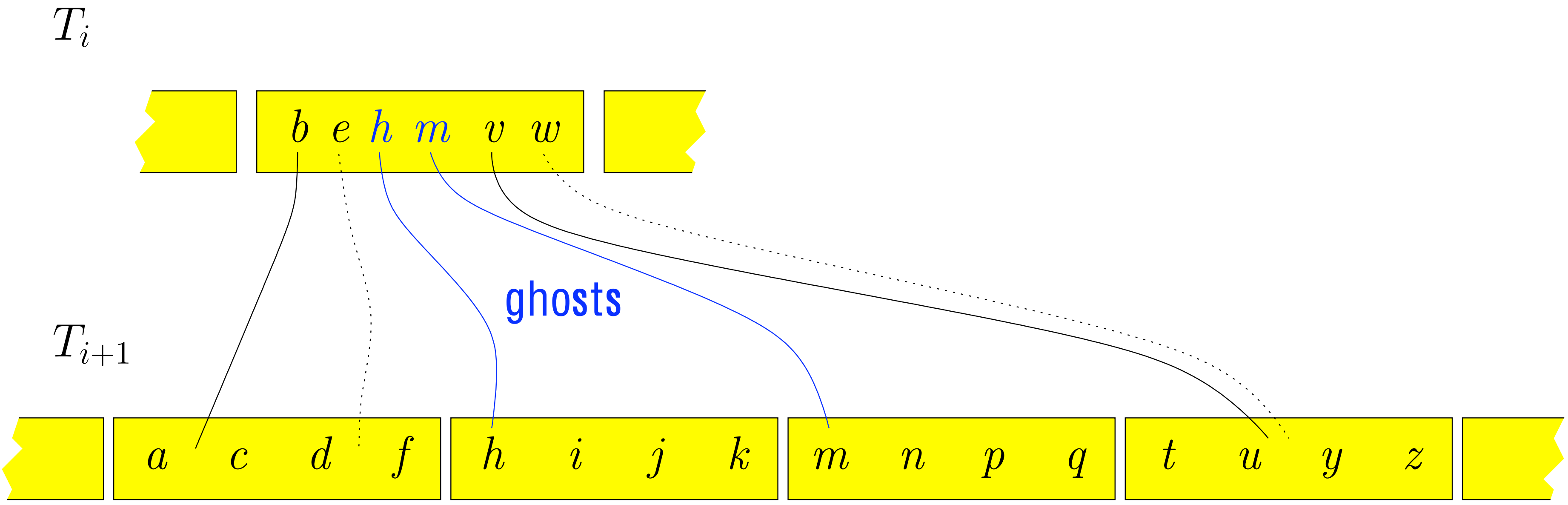
Remove redundant forwarding pointers

We need only one forwarding pointer for each block in the next tree. Remove the redundant ones.



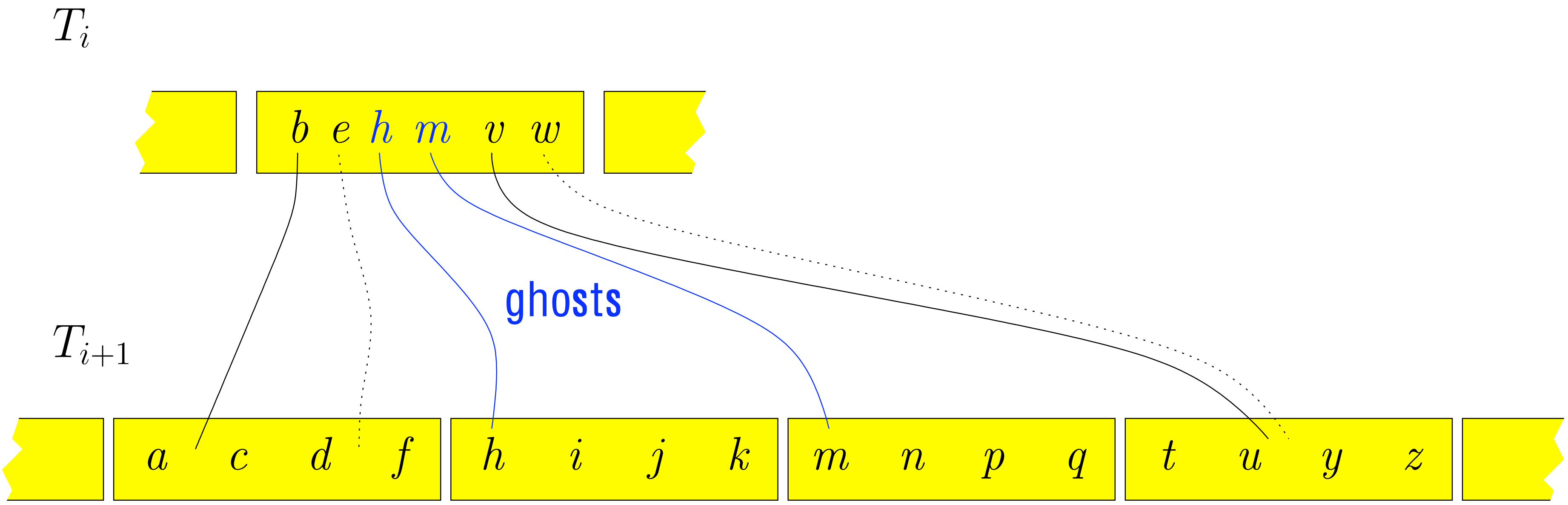
Ghost pointers

We need a forwarding pointer for every block in the next tree, even if there are no corresponding pointers in this tree. Add ghosts.



LSM tree + forward + ghost = fast queries

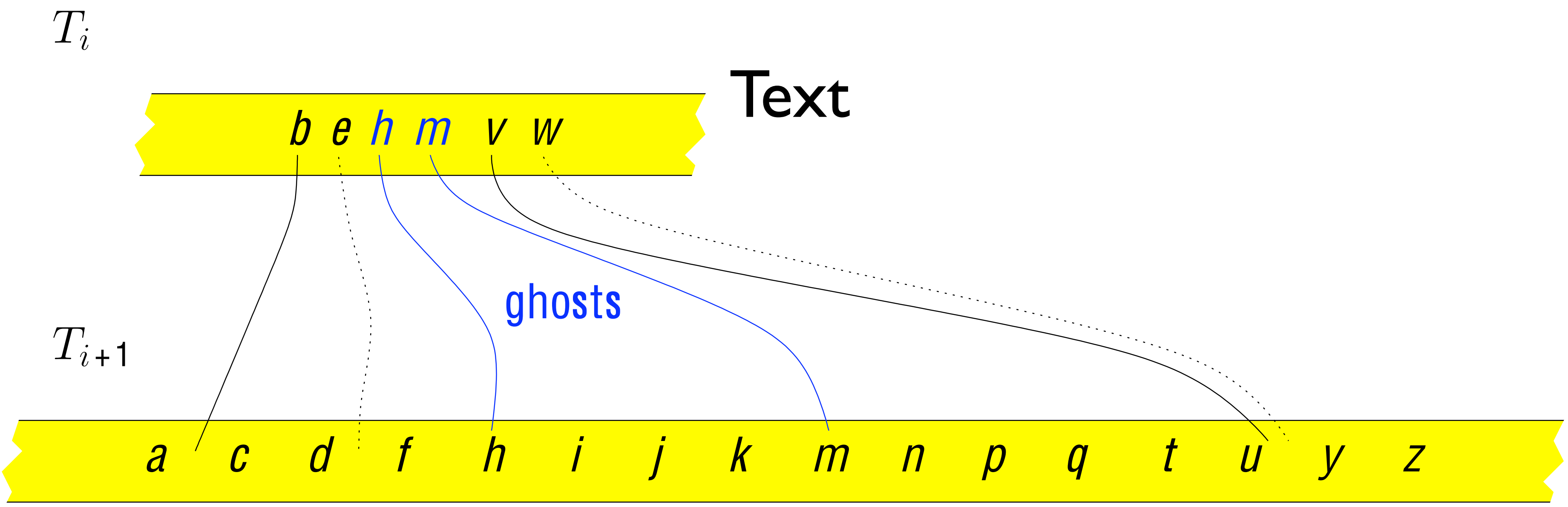
With forward pointers and ghosts, LSM trees require only one I/O per tree, and point queries cost only $O(\log_R N)$**.**



[Bender, Farach-Colton, Fineman, Fogel, Kuszmaul, Nelson 07]

LSM tree + forward + ghost = COLA

This data structure no longer uses the internal nodes of the B-trees, and each of the trees can be implemented by an array.



[Bender, Farach-Colton, Fineman, Fogel, Kuszmaul, Nelson 07]

Data Structures and Algorithms for Big Data

Module 7: Bloom Filters

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Approximate Set Membership Problem

We need a space-efficient in-memory data structure to represent a set *S* to which we can add elements. We want to answer *membership queries* approximately:

- If *x* is in *S* then we want query(*x*,*S*) to return true.
- Otherwise we want query(*x*,*S*) to usually return false.

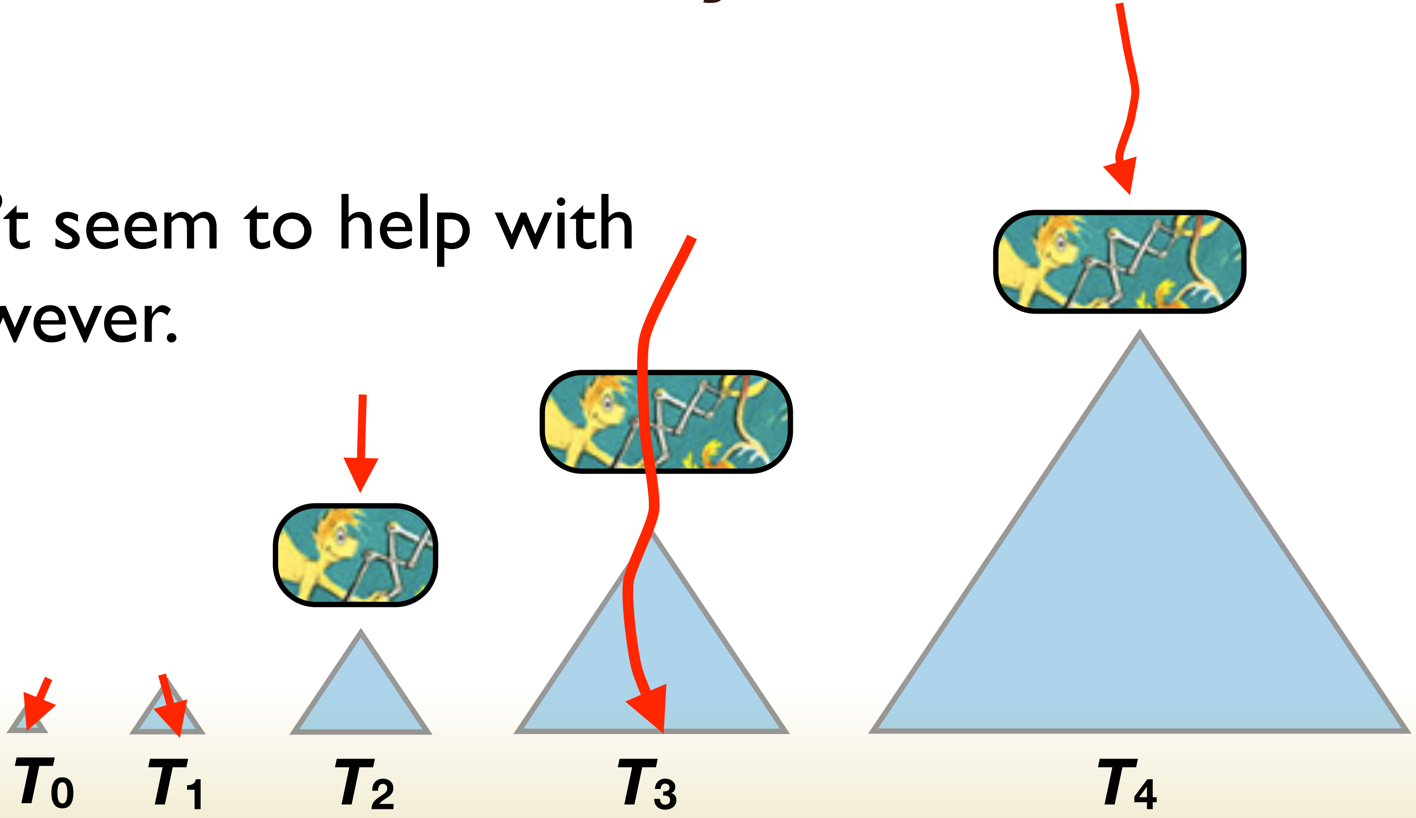
Bloom filters are a simple data structure to solve this problem.

How do approximate queries help?

Recall for LSM trees (without fractional cascading), we wanted to avoid looking in a tree if we knew a key wasn't there.

Bloom filters allow us to *usually* avoid the lookup.

Bloom filters don't seem to help with range queries, however.



Simplified Bloom Filter

Using hashing, but instead of storing elements we simply use one bit to keep track of whether an element is in the set.

- Array $A[m]$ bits.
- Uniform hash function h: S --> $[0,m)$.
- To insert s: Set $A[h(s)] = 1$;
- To check s: Check if $A[h(s)]=1$.

Example using Simplified Bloom Filter

Use an array of length 6. Insert

- insert *a*, where *h*(*a*)=3;
- *b*, where *h*(*b*)=5.

0	1	2	3	4	5
0	0	0	1	0	1

Look up

- *a*: *h*(*a*)=3 Answer is yes. Maybe *a* is there. (And it is).
- *b*: *h*(*b*)=5 Answer is yes. Maybe *b* is there. (And it is).
- *c*: *h*(*c*)=2 Answer is no. Definitely *c* is not there.
- *d*: *h*(*d*)=3 Answer is yes. Maybe *d* is there. (Nope.)

Analysis of Simplified Bloom Filter

If *n* items are in an array of size *m,* then the chances of getting a YES answer on an element that is not there is $\approx 1 - e^{-n/m}$.

If you fill the array about 30% full, you get about a 50% odds of a false positive. Each object requires about 3 bits.

How do you get the odds to be 1% false positive?

Smaller False Positive

One way would be to fill the array only 1% full.

Not space efficient.

Another way would be to use 7 arrays, with 7 hash functions. False positive rate becomes 1/128.

Space is 21 bits per object.

Bloom filter

Idea: Don’t use 7 separate arrays, use one array that’s 7 times bigger, and store the 7 hashed bits.

For a 1% false positive rate, it takes about 10 bits per object.

Other Bloom Filters

Counting bloom filters [Fan, Cao, Almeida, Broder 2000] allow deletions by maintaining a 4-bit counter instead of a single bit per object.

Buffered Bloom Filters [Canin, Mihaila, Bhattacharhee, and Ross, 2010] employ hash localization to direct all the hashes of a single insertion to the same block.

Cascade Filters [Bender, Farach-Colton, Johnson, Kraner, Kuszmaul, Medjedovic, Montes, Shetty, Spillane, Zadok 2011] support deletions, exhibit locality for queries, insert quickly, and are cache-oblivious.

Closing Words

We want to feel your pain.

We are interested in hearing about other scaling problems.

Come to talk to us.

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bradley@mit.edu

Big Data Epigrams

The problem with big data is microdata.

Sometimes the right read optimization is a write-optimization.

As data becomes bigger, the asymptotics become more important.

Life is too short for half-dry white-board markers and bad sushi.