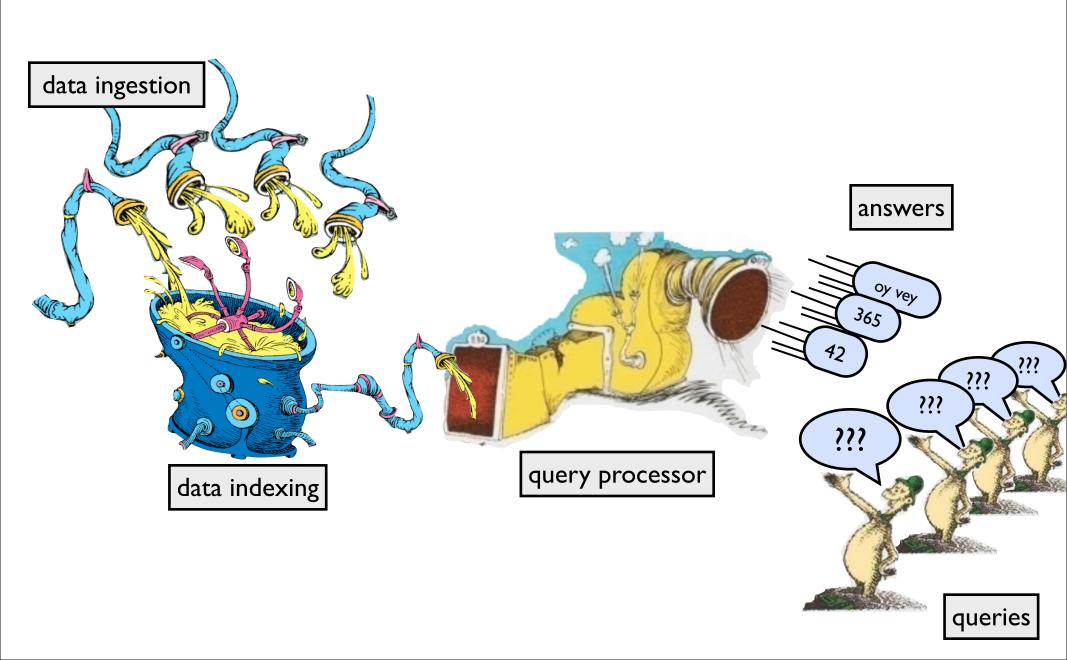


#### **Indexing Big Data**



Michael A. Bender



# The problem with big data is microdata

Microdata is small data.

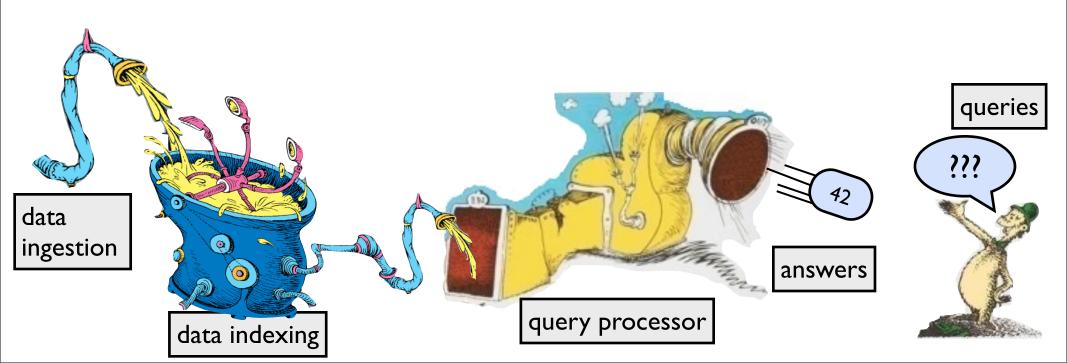
The most intractable data consists of lots of small pieces.



# Microdata is everywhere

#### Metadata≈microdata.

Even when data has big chunks, metadata is small.



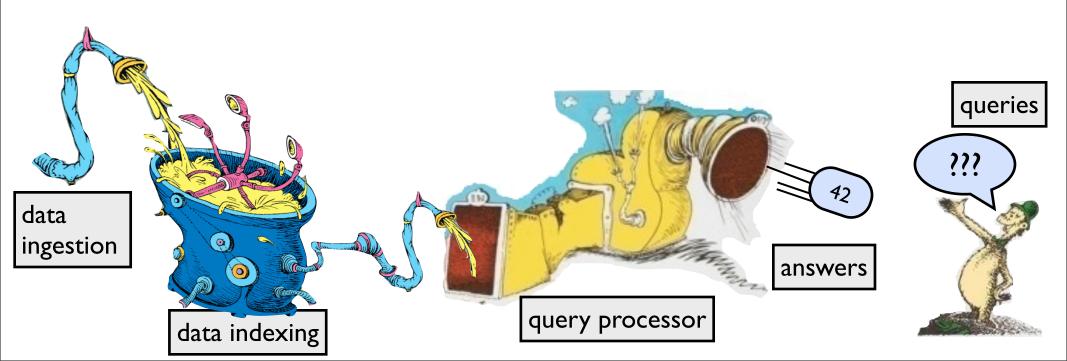
# Microdata is everywhere

#### Metadata≈microdata.

Even when data has big chunks, metadata is small.

#### Small files in parallel/cloud file systems.

• HPC workloads use the names of many small files, e.g., to describe experiment metadata.



# Microdata is everywhere

answers

#### Metadata≈microdata.

data indexing

Even when data has big chunks, metadata is small.

#### Small files in parallel/cloud file systems.

 HPC workloads use the names of many small files, e.g., to describe experiment metadata.

#### Small updates inside large files.

query processor

### The microdata problem is getting worse

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

log 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 IK)
1973	35MB	835KB/s	25ms	39s	975s
2010	3TB	I50MB/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.

# HEC FSIO Grand Challenges

Store 1 trillion files

Create tens of thousands of files per second

Traverse directory hierarchies fast (1s -R)

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

# HEC FSIO Grand Challenges

Store 1 trillion files

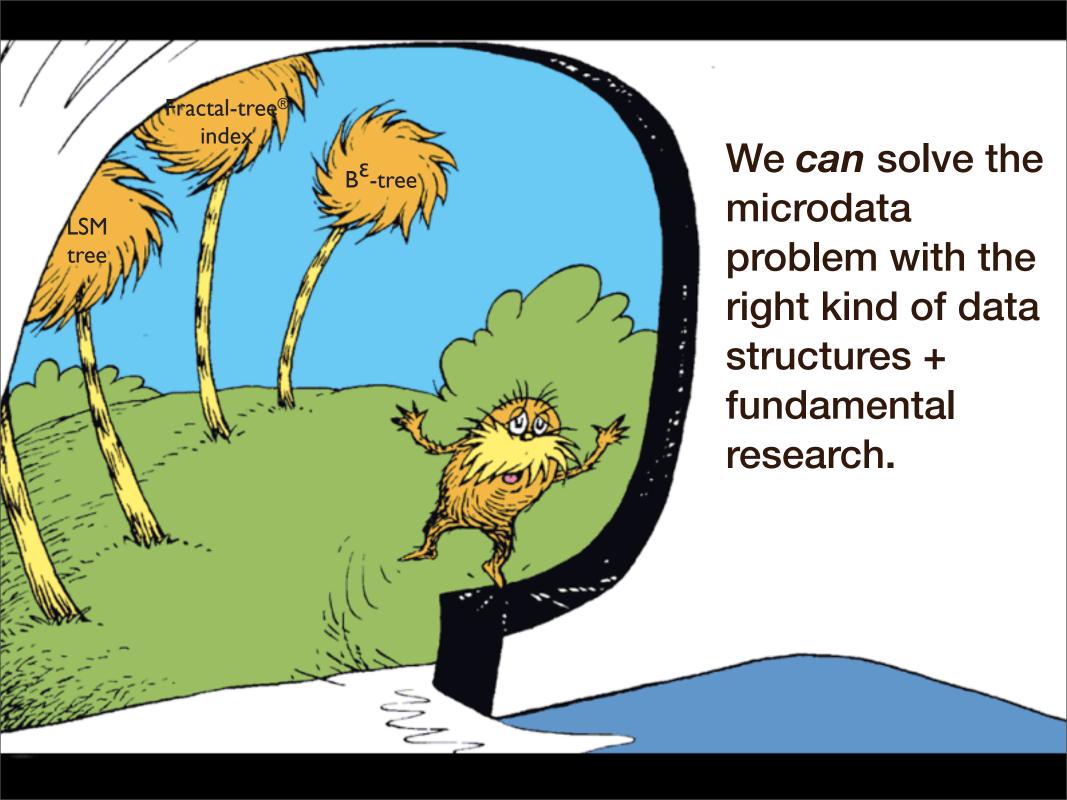
Create tens of thousands of files per second

Traverse directory hierarchies fast (1s -R)

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

Parallel computing is about high performance. To get high performance, we need high-performance I/O.





## Write-optimized data structures can help

**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	$O(\log_B N) = O(\frac{\log N}{\log B})$	$O(\frac{\log N}{B})$

- 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 because microdata is transferred in parallel in data blocks.

# Optimal Search-Insert Tradeoff

[Brodal, Fagerberg 03]

#### insert

#### point query

# Optimal tradeoff

$$O\left(\frac{\log_{1+B^{\varepsilon}} N}{B^{1-\varepsilon}}\right)$$

$$O\left(\log_{1+B^{\varepsilon}} N\right)$$

$$(l=3)$$

$$O\left(\log_B N\right)$$

$$O(\log_B N)$$

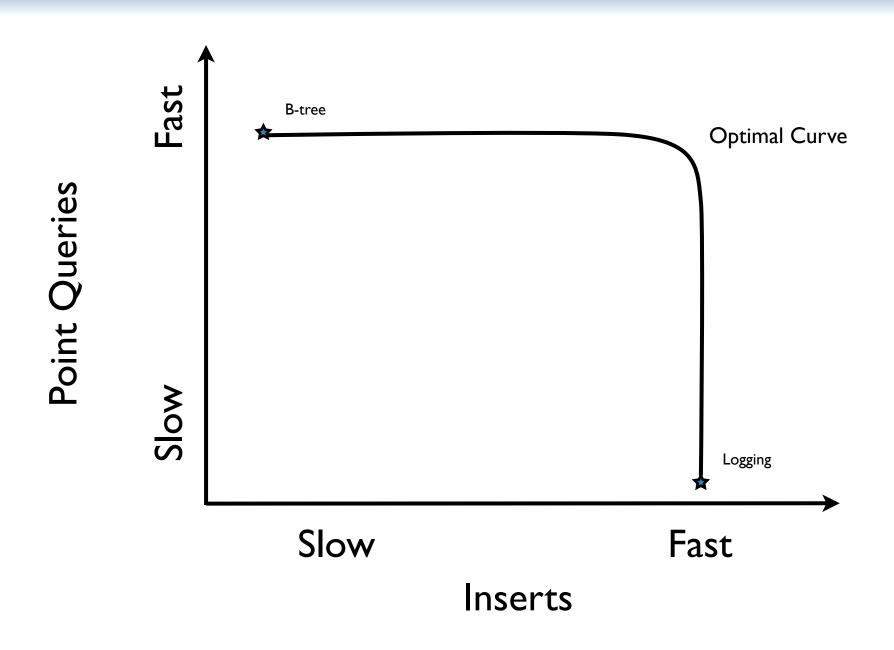
$$\varepsilon = 1/2$$

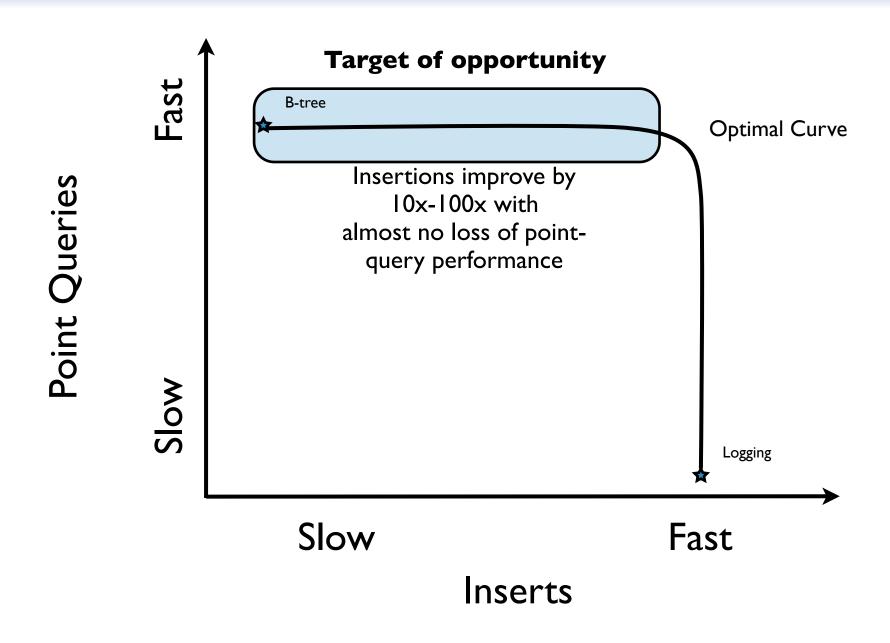
$$O\left(\frac{\log_B N}{\sqrt{B}}\right)$$

$$O(\log_B N)$$

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

$$O(\log N)$$





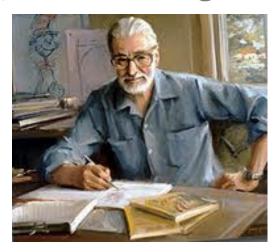
# What the world looks like and research directions

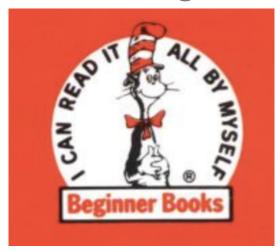
#### What the world looks like

#### 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.



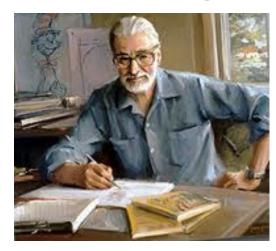


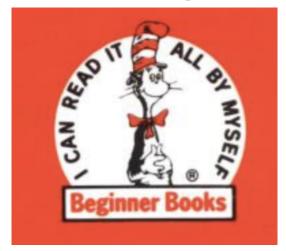
#### What the world looks like

#### 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.



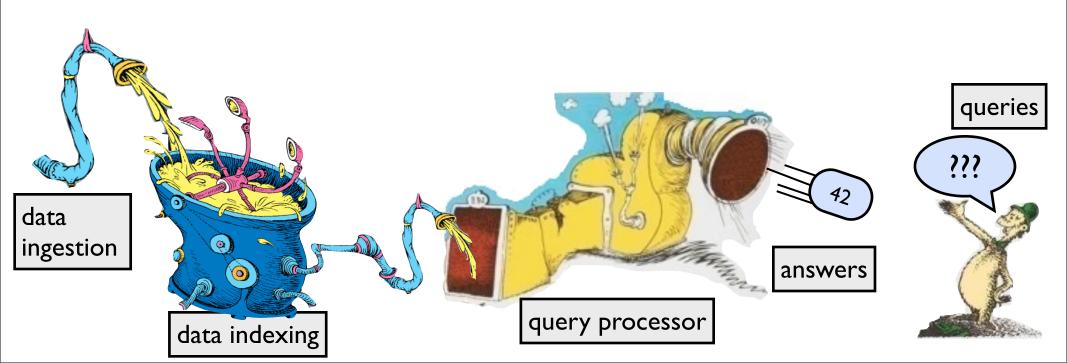


How can we revisit system design in light of this asymmetry?

### The best read-optimization is write-optimization

# The right index (e.g., database index=data ordering) makes queries run fast.

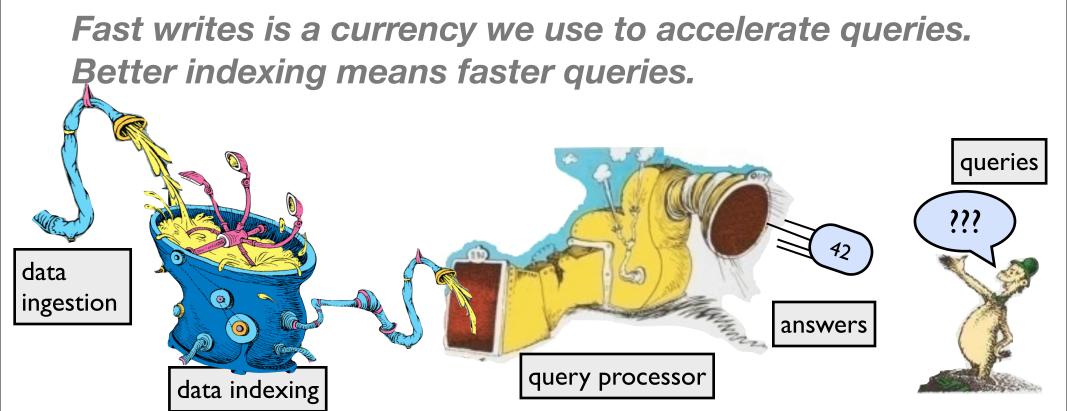
- E.g., *find* or *spotlight* on a file system can be fast if the data is indexed correctly.
- Write-optimized structures maintain indexes efficiently.

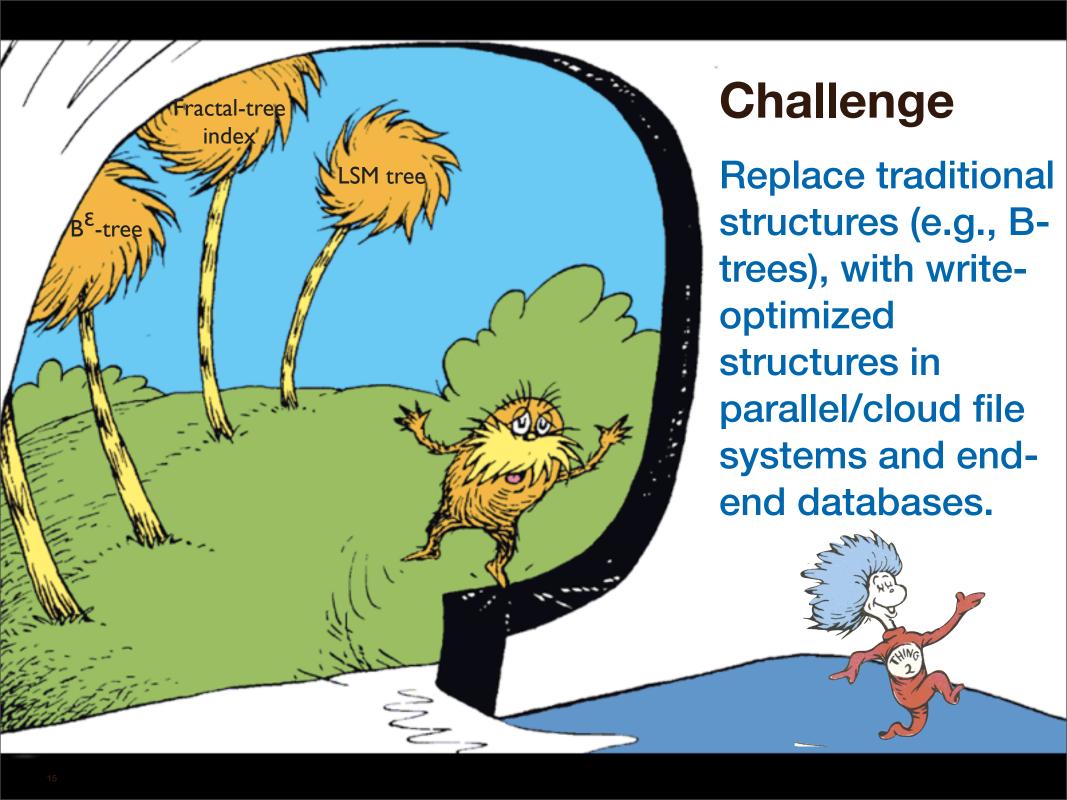


### The best read-optimization is write-optimization

# The right index (e.g., database index=data ordering) makes queries run fast.

- E.g., *find* or *spotlight* on a file system can be fast if the data is indexed correctly.
- Write-optimized structures maintain indexes efficiently.





### Our progress building write-optimized systems

#### **TokuDB**

- A write-optimized storage engine for the MySQL
- Commercial product from Tokutek

#### **TokuFS**

[Esmet, Bender, Farach-Colton, Kuszmaul 12]

- A file-system prototype
- >20K file creates/sec
- very fast ls -R
- HEC grand challenges on a cheap disk

### 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.

 Write-optimized data structures run quickly because inserts don't put elements directly in their final positions, so that you can insert without incurring a disk I/O, even in the worst case and for large data sets.

# Redesign systems in light of search/point query asymmetry

#### Redesign systems to avoid cryptosearches.

- Design new algorithms for concurrency control, transactional mechanisms, crash safety, etc, in light of the new performance characteristics.
- Redesign existing APIs.

#### Some cryptosearches, cannot be avoided.

• How can we mitigate their damage (e.g., Bloom filters, SSDs)?

#### Highly parallel/concurrent write-optimized structures

Write-optimized structures are CPU-bound even for workloads on which traditional storage systems are I/O bound.

Need highly concurrent, multithreaded writeoptimized data structures.



# Summary of Talk

#### Microdata in parallel and high-end computing:

We need high-performance I/O.

#### How foundational parallelism research helps:

- Better write-optimized data structures.
- Lower bounds.
- Algorithms for concurrency control, transactions.
- Multithreading + high concurrency.

