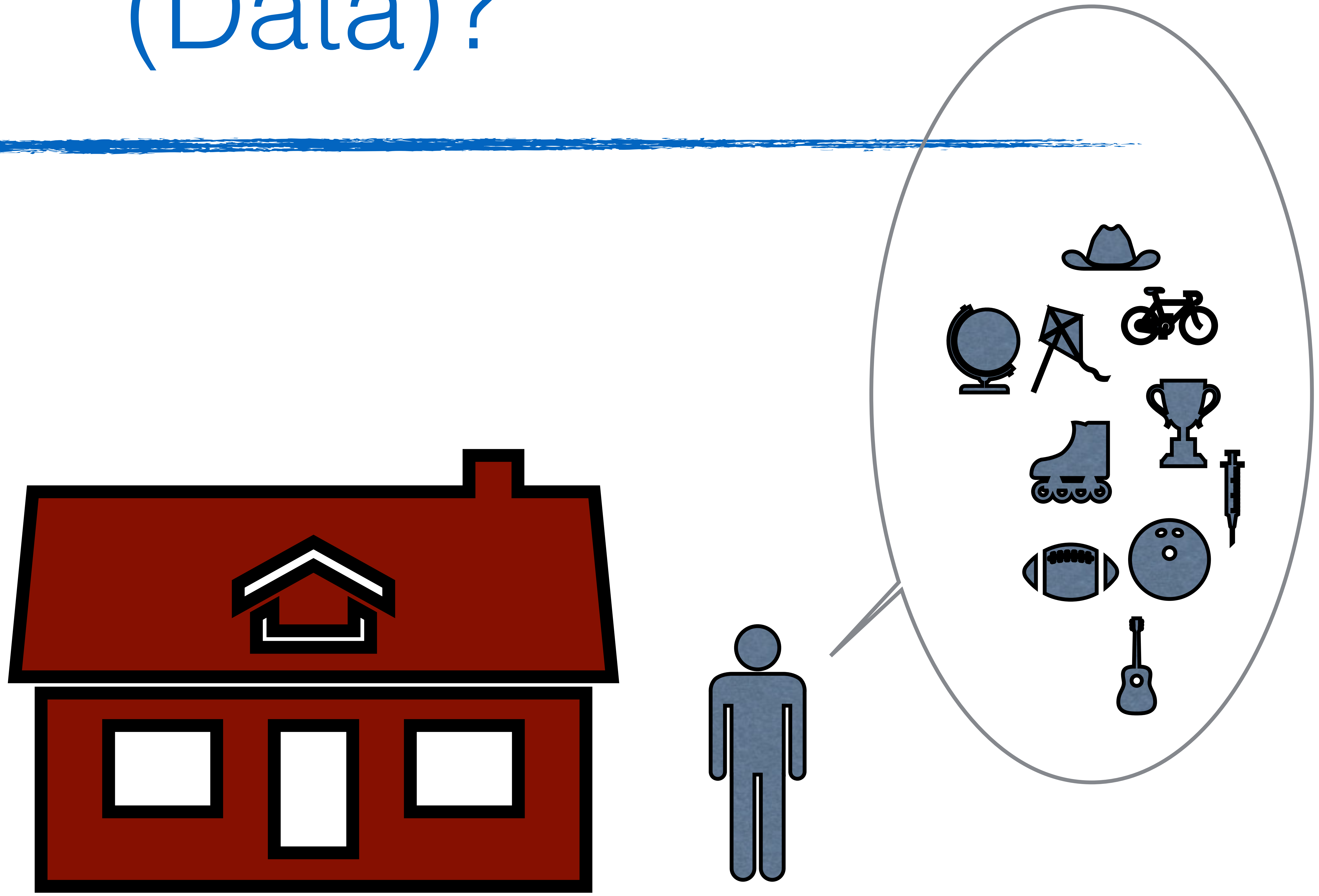
# Log-Structured Merge Trees

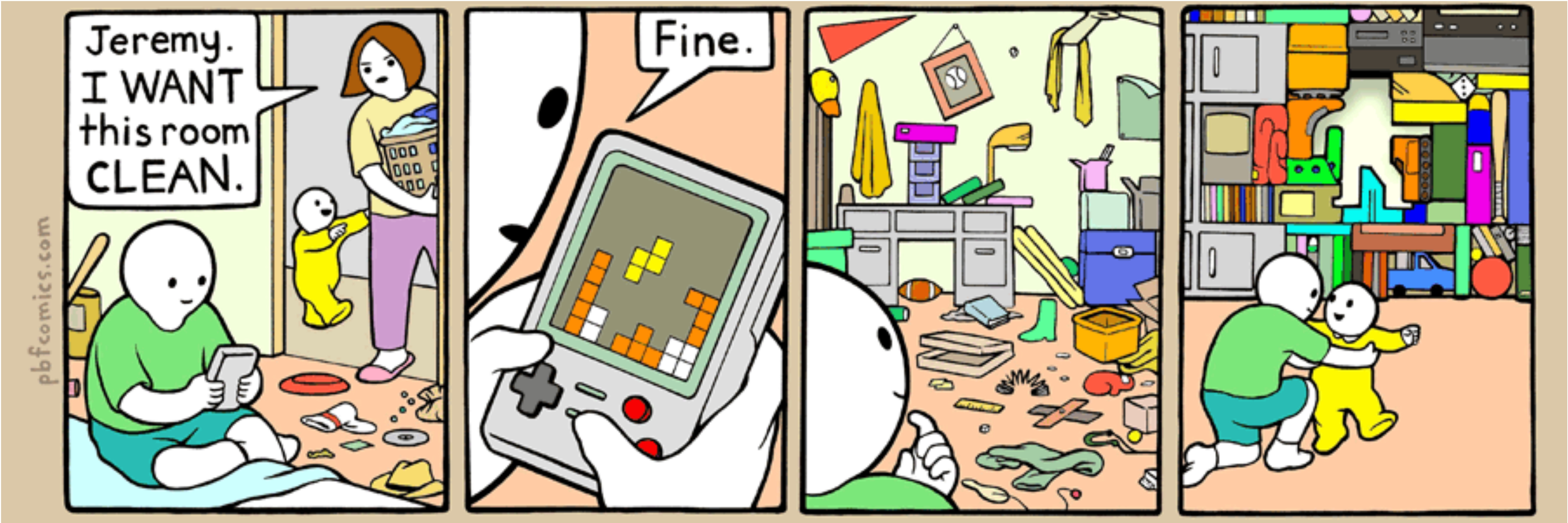
**CSCI 333**

# How Should I Organize My Stuff (Data)?



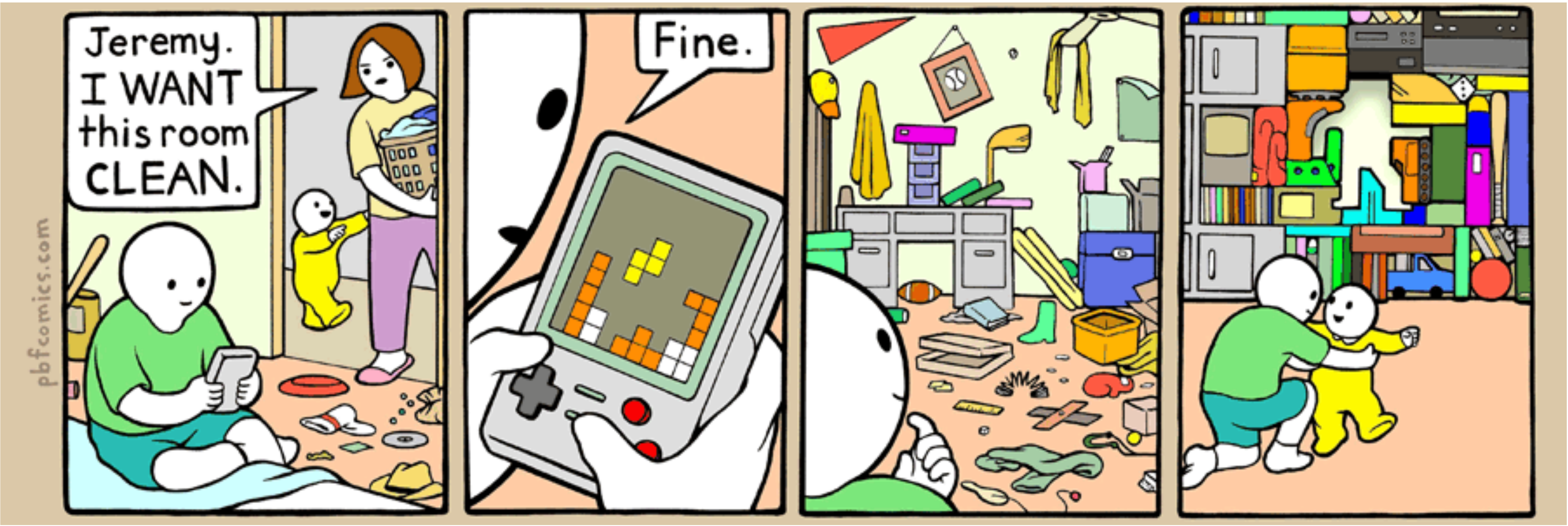
# How Should I Organize My Data?

**Different people approach the problem differently…**




[https://pbfcomics.com/comics/game-boy/]

# How Should I Organize My Data?




Logging

Indexing

# How Should I Organize My Data?

| | Logging | Indexing |
|---|---|---|
| Inserting | Append at end of log | Insert at leaf (traverse root-to-leaf path) |
| Searching | Scan through entire log | Locate in leaf (traverse root-to-leaf path) |

# How Should I Organize My Data?

| | Logging | Indexing |
|---|---|---|
| Inserting | $O(1/B)$ | $O(\log_B N)$ |
| Searching | $O(N/B)$ | $O(\log_B N)$ |

Assuming B-tree

# Are We Forced to Choose?

**It appears we have a tradeoff between insertion and searching**

- B-trees have
  - fast searches: $O(\log_B N)$ is the optimal search cost
  - slow inserts
- Logging has
  - fast insertions
  - slow searches: cannot get worse than exhaustive scan

# Goal: Data Structural Search for Optimality

**B-tree searches are optimal**

**B-tree updates are not**

- We want a data structure with inserts that beat B-tree inserts without sacrificing on queries

**> This is the promise of write-optimization**

# Log-Structured Merge Trees

**Data structure proposed by O'Neil,Cheng, and Gawlick in 1996**

- Uses write-optimized techniques to significantly speed up inserts

**Hundreds of papers on LSM-trees (both innovating and using)**

**To get some intuition for the data structure, let's break it down**

Log-structured • Merge • Tree

# Log-Structured Merge Trees

## Log-structured

- All data is written sequentially, regardless of temporal ordering

Merge • Tree

# Log-Structured Merge Trees

## Log-structured

- All data is written sequentially, regardless of temporal ordering

## Merge

- As data evolves, sequentially written runs of key-value pairs are merged
  - Runs of data are indexed for efficient lookup
  - Merges happen only after much new data is accumulated

## Tree

# Log-Structured Merge Trees

## Log-structured

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- As data evolves, sequentially written runs of key-value pairs are merged
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## Tree

- The hierarchy of key-value pair runs form a tree
  - Searches start at the root, progress downwards

# Log-Structured Merge Trees

**Start with [O'Neil 96], then describe LevelDB**

**We will discuss:**

- Compaction strategies
- Notable "tweaks" to the data structure
- Commonly cited drawbacks
- Potential applications

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

**An LSM-tree comprises a hierarchy of trees of increasing size**

- *All* data inserted into in-memory tree ($C_0$)
- Larger on disk trees ($C_{i>0}$) hold data that does not fit into memory

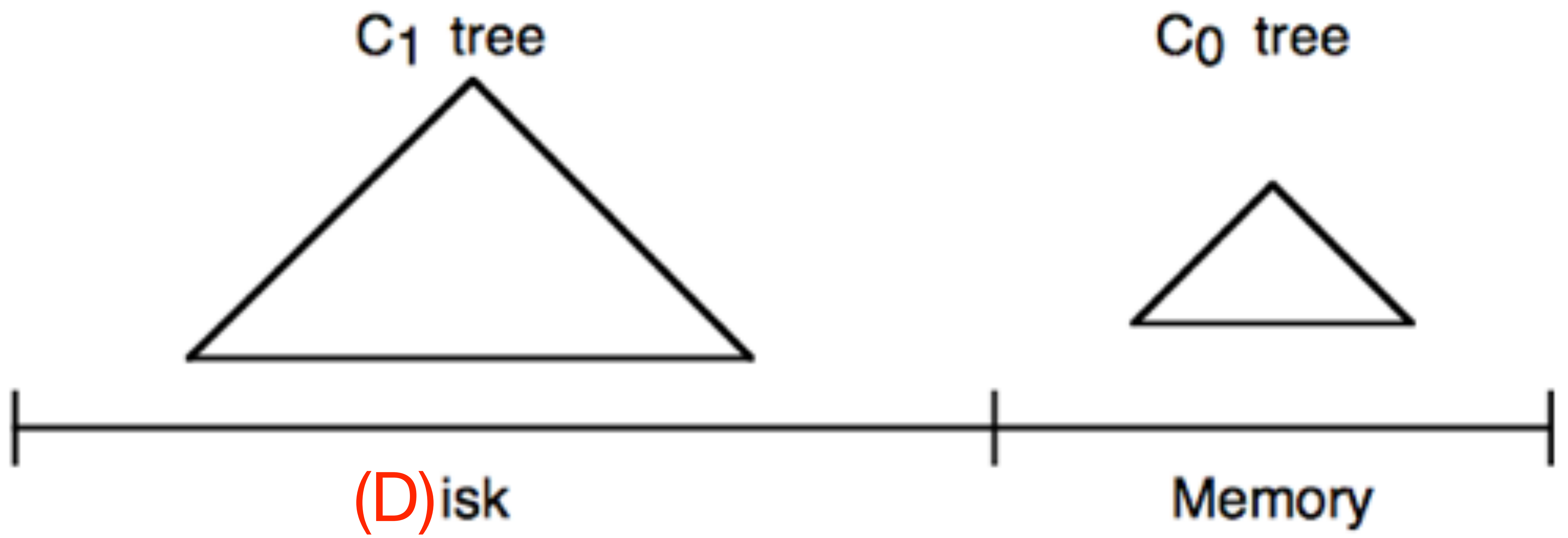



**Figure 2.1.** Schematic picture of an LSM-tree of two components

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

**When a tree exceeds its size limit, its data is merged and rewritten**

- Higher level is always merged into next lower level ($C_i$ merged with $C_{i+1}$)
  - Merging always proceeds top down

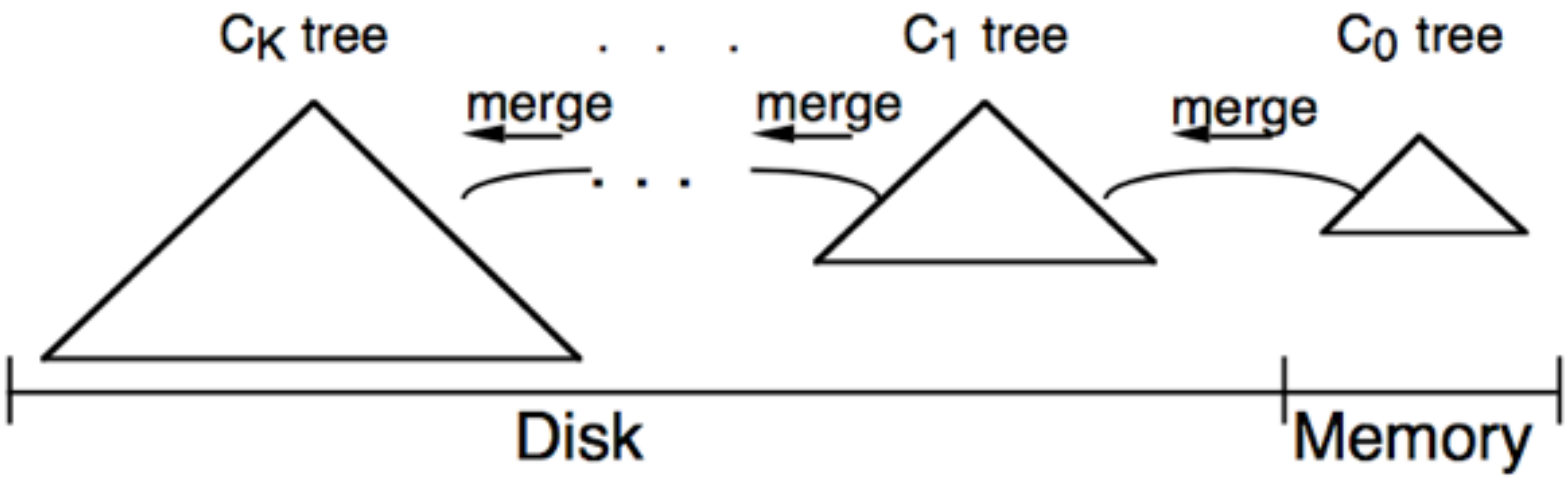



**Figure 3.1.** An LSM-tree of K+1 components

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

- Recall mergesort from data structures
  - We can efficiently merge two sorted structures
- When merging two levels, newer version key-value pair replaces older (GC)
  - LSM-tree invariant: newest version of any key-value pair is version nearest to top of LSM-tree

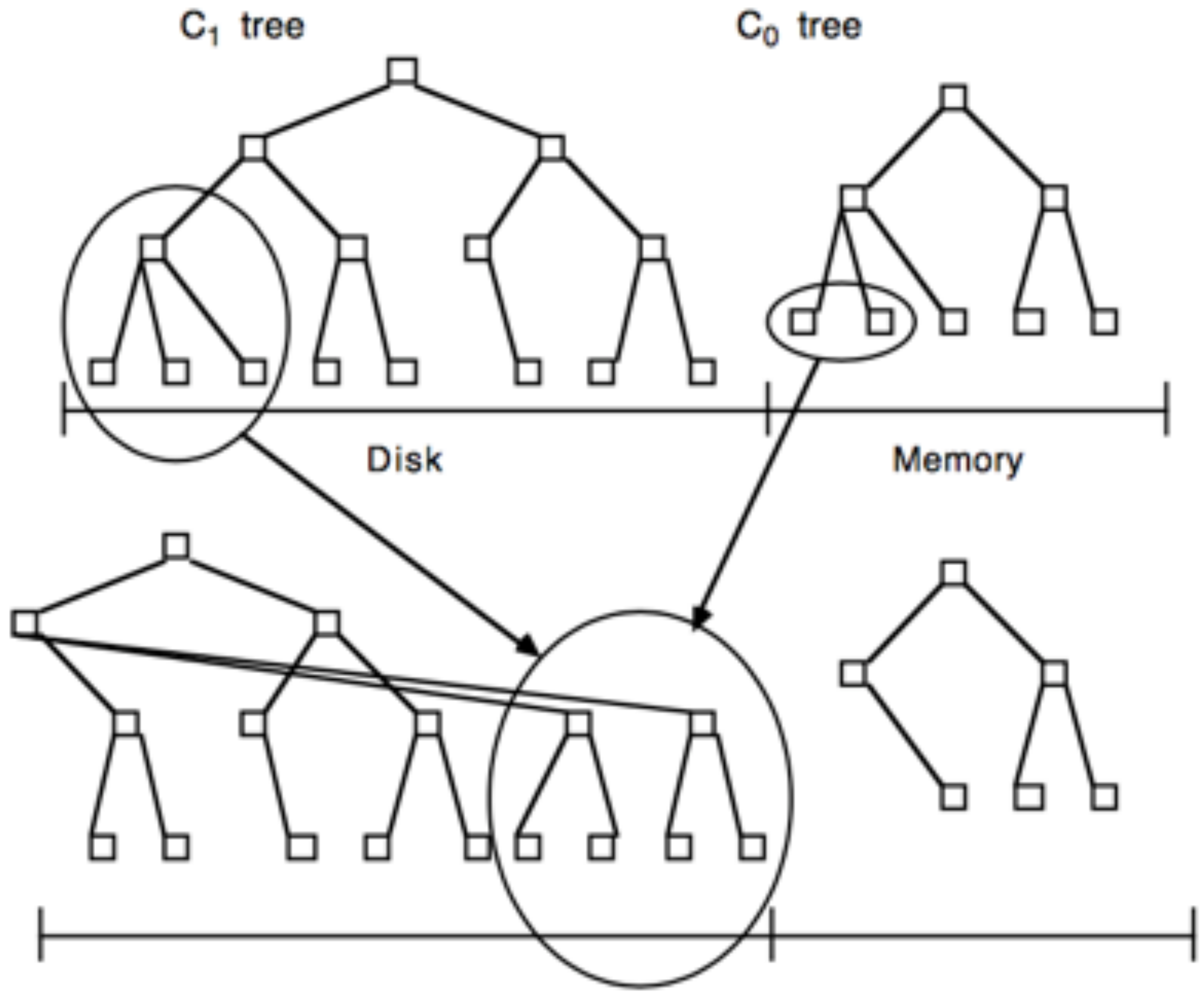



**Figure 2.2.** Conceptual picture of rolling merge steps, with result written back to disk

# LSM-trees are another dictionary data structure

## Maintain a set of key-value pairs (kv pairs)

- Support the dictionary interface
  - `insert(k, v)` - insert a new kv pair, (possibly) replacing old value
  - `delete(k)` - remove all values associated with key `k`
  - `(k,v) = query(k)` - return latest value **v** associated with key `k`
  - $\{(k_1, v_1), (k_2, v_2), \ldots, (k_j, v_j)\}$ = `query(`$k_i$`, `$k_l$`)` - return all key-value pairs in the range from $k_i$ to $k_l$

> **Question: How do we implement each of these operations?**

# Insert(k)

**We insert the key-value pair into the in-memory level, $C_0$**

- Don't care about lower levels, as long as newest version is one closest to top
- But if an old version of kv-pair exists in the top level, we must replace it
- If $C_0$ exceeds its size limit, compact (merge)

> **Inserts are fast! Only touch $C_0$.**

# Delete(k)

**We insert a tombstone into the in-memory level, $C_0$**

- A tombstone is a "logical delete" of all key-value pairs with key ***k***
  - When we merge a tombstone with a key-value pair, we delete the key-value pair
  - When we merge a tombstone with a tombstone, just keep one
  - When can we delete a tombstone?
    - At the lowest level
    - When merging a *newer* key-value pair with key ***k***

**> Deletes are fast! Only touch $C_0$.**

# Query(k)

## Begin our search in the in-memory level, $C_0$

- Continue until:
  - We find a key-value pair with key ***k***
  - We find a tombstone with key ***k***
  - We reach the lowest level and fail-to-find

**> Searches traverse (worst case) every level in the LSM-tree**

# Query($k_j$, $k_l$)

**We must search *every* level, $C_0 \ldots C_n$**

- Return all keys in range, taking care to:
  - Return newest **($k_i$, $v_i$)** where $k_j < k_i < k_l$ such that there are no tombstones with key $k_i$ that are newer than **($k_i$, $v_i$)**

**> Range queries must scan every level in the LSM-tree (although not all ranges in every level)**

# LevelDB

Google's Open Source *LSM-tree-ish* KV-store

# Some Definitions

## LevelDB consists of a hierarchy of SSTables

- An SSTable is a sorted set of key-value pairs (Sorted Strings Table)
  - Typical SSTable size is 2MiB

## The growth factor describes how the size of each level scales

- Let $F$ be the growth factor (fanout)
- Let $M$ be the size of the first level (e.g., 10MiB)
- Then the $i^{th}$ level, $C_i$ has size $F^i M$

## The spine stores metadata about each level

- {$\mathbf{key}_i$, $\mathbf{offset}_i$} for a all SSTables in a level (plus other metadata TBD)
- Spine cached for fast searches of a given level
  - (if too big, a B-tree can be used to hold the spine for optimal searches)

# LevelDB Example

# LevelDB Example


1. Write operation to log (immediate persistence)
2. Update in-memory SSTable
3. (Eventually) promote full SSTable and initialize new empty SSTable
4. Merge/write in-memory SSTables to $L_0$

# Compaction

## How do we manage the levels of our LSM?

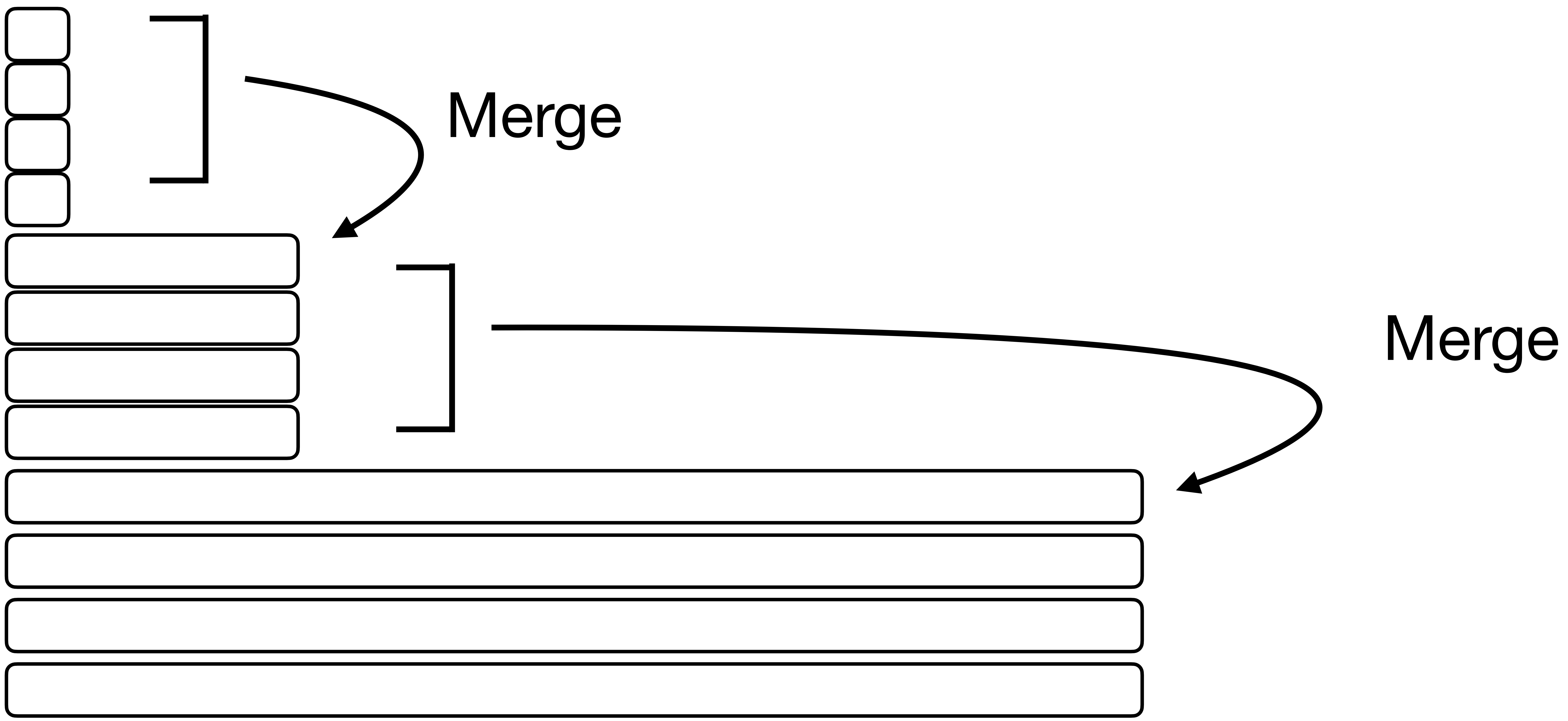
- Ideal data management strategy would:
  - Write all data sequentially for fast inserts
  - Keep all data sorted for fast searches
  - Minimize the number of levels we must search per query (low read amplification)
  - Minimize the number of times we write each key-value pair (low write amplification)

- Good luck making that work!
  - … but let’s talk about some common approaches

# Write-optimized Data Structures

## Option 1: Size-tiered

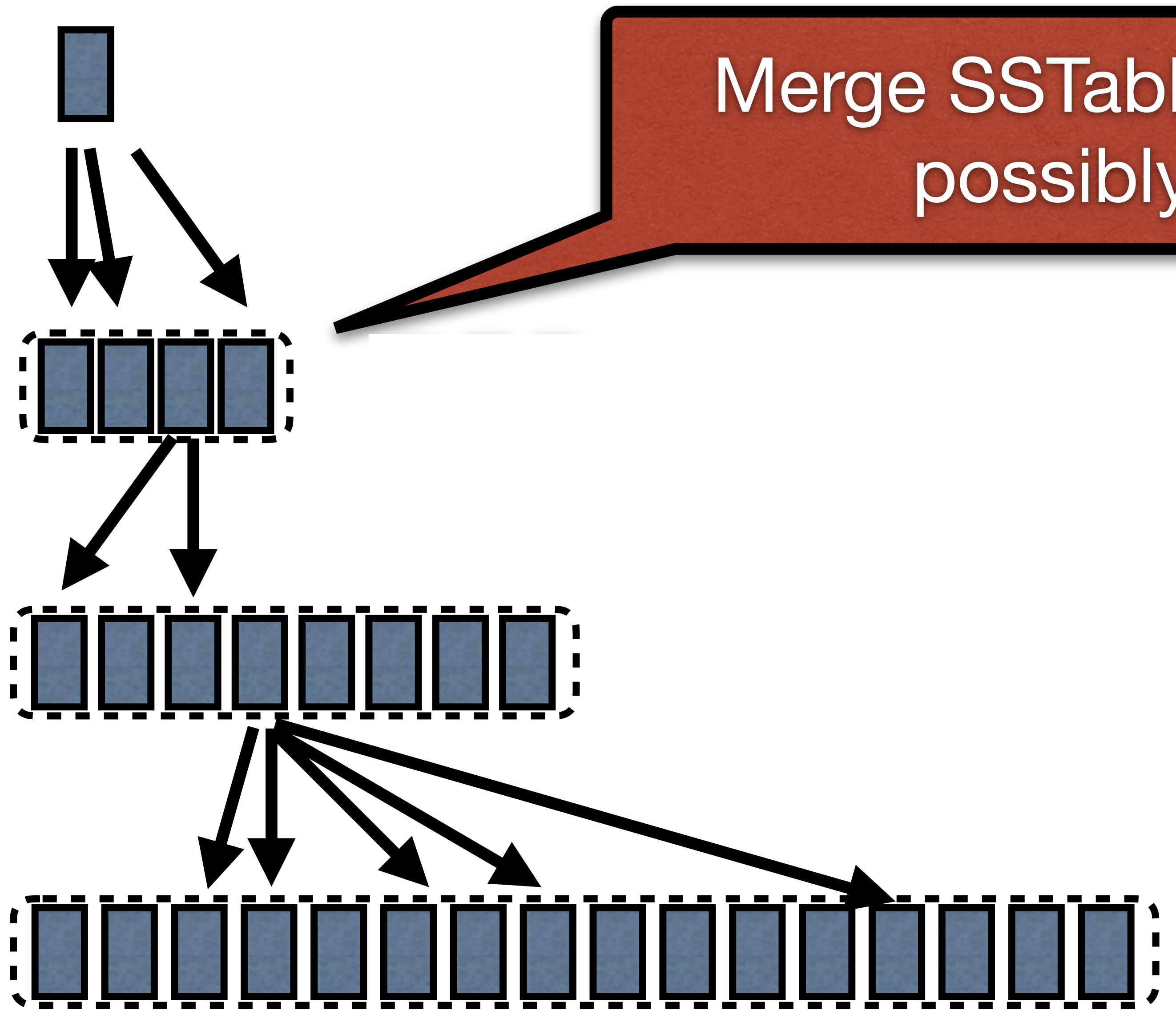
- Each "tier" is a collection SSTables with similar sizes
- When we compact, we merge some number of SSTables with the same size to create an SSTable in the next tier



# Write-optimized Data Structures

## Option 2: Level-tiered

- All SSTables are fixed size
- Each level is a collection SSTables with non-overlapping key ranges
- To compact, pick SSTable(s) from $L_i$ and merge them with SSTables in $L_{i+1}$
  - Rewrite merged SSTables into $L_{i+1}$ (redistributing key ranges if necessary)
  - Possibly continue (cascading merge) of $L_{i+1}$ to $L_{i+2}$
  - Several ways to choose (e.g., round-robin or ChooseBest)
    - Possibly add invariants to our LSM to control merging (e.g., an SSTable at $L_{i+1}$ can cover at most X SSTables at $L_{i+1}$)



# LSM-tree Problems?

## We write a lot of data during compaction

- Not all data is new
  - We may rewrite a key-value pair to the same level multiple times
- How might we save extra writes?
  - VT-trees [Shetty FAST '13]: if a long run of kv-pairs would be rewritten unchanged to the next level, instead write a pointer
- Problems with VT-trees?
  - Fragmentation
    - Scanning a level might mean jumping up and down the tree, following pointers

> **There is a tension between locality and rewriting**

# LSM-tree Problems?

## We write a lot of data during compaction

- Not all data is new
  - We may rewrite a key-value pair to the same level multiple times
- How might we save extra writes?
  - Fragmented LSM-Tree [Raju SOSP '17]: each level can contain up to *F* fragments
  - Fragments can be appended to a level without merging with SSTables in that level
    - Saves the work of doing a "merge" until there is enough work to justify the I/Os

- Problems with fragments?
  - Fragments can have overlapping key ranges, so may need to search through multiple fragments
  - Need to be careful about returning newest values

**> Again, we see a tension between locality and rewriting**

# LSM-tree Problems?

## We write a lot of data during compaction

- Work "builds up", and small writes might trigger a lot of I/O for this pent-up work
  - We often care about **tail latency** in real systems (the latency of the worst N% of operations)
  - We often care about performance predictability

> **Amortization is great for throughput, but burstiness harms individual operations**

# LSM-tree Problems?

## We read a lot of data during searches

- We may need to search every level of our LSM-tree
  - Binary search helps (SSTables are sorted), but still many I/Os to check all relevant SSTables in all levels
- How might we save extra reads?
  - Bloom filters!
  - By adding a Bloom filter, we only search if the data exists in that level (or false positive)
  - Bloom filters for large data sets can fit into memory, so approximately `1+e` I/Os per query
    - Recent work dynamically “reallocates” bits to minimize false positives for a given memory budget
- Problems with Bloom filters?
  - Do they help with range queries?
    - Not really…

# Thought Questions

## How might you design:

- an LSM-tree for an SSD?
- an LSM-tree for an SMR drive?
  - how would your designs be different?
    - Scale (SSD blocks are much smaller than SMR zones)
    - Different concerns (e.g., wear leveling & endurance, parallelism)

## We talked about storing the data with your index, or separating your data from your index (clustered vs. declustered index)

- How might you design a system that separates keys from values?
  - Wisckey [Lu FAST 16]: Store keys in LSM-tree, values in a log
- What are the advantages/disadvantages?
  - Can fit most of the LSM-tree (keys) in memory -> 1 I/O per search
  - Need to GC your value log, just like LFS