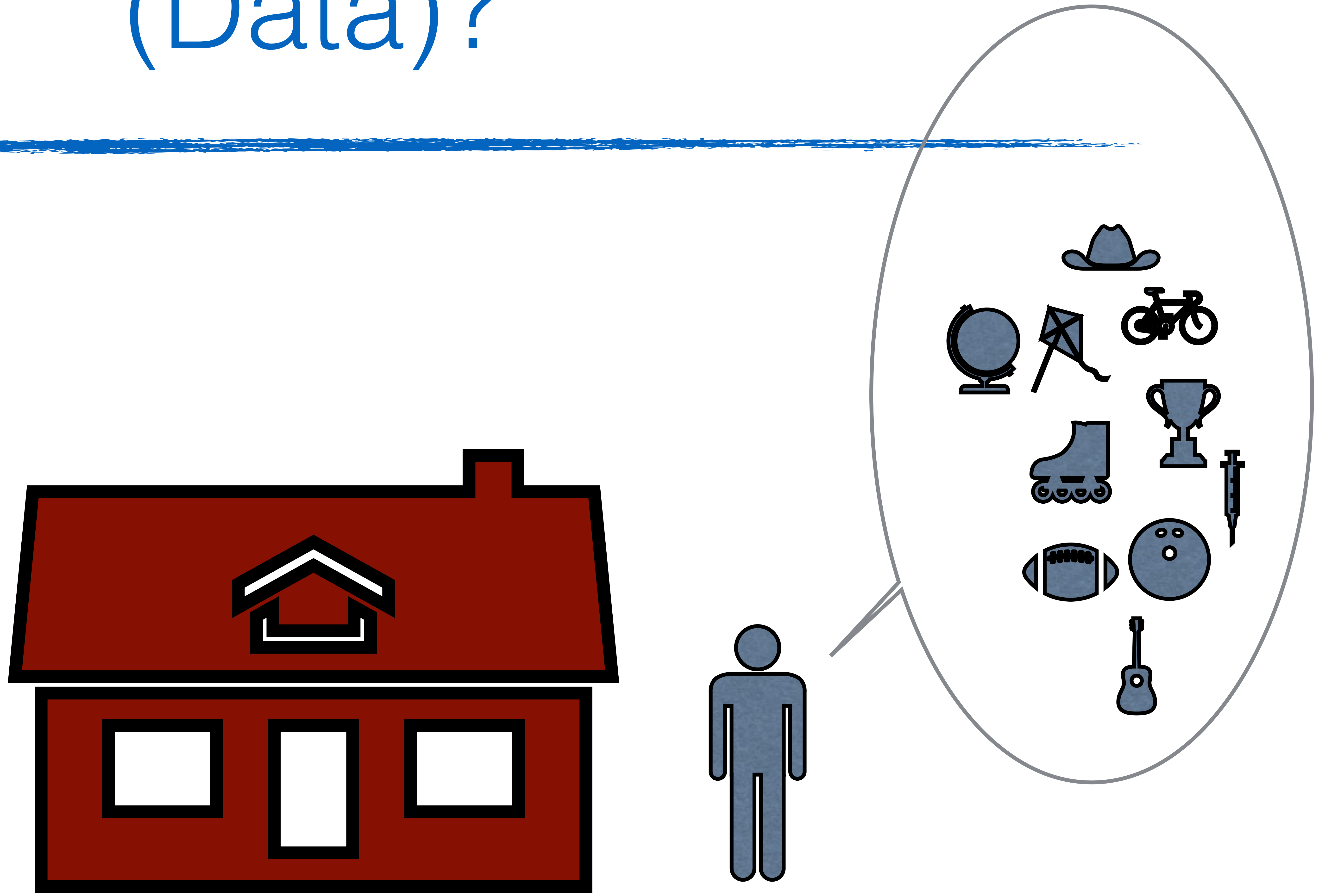
Log-Structured Merge Trees

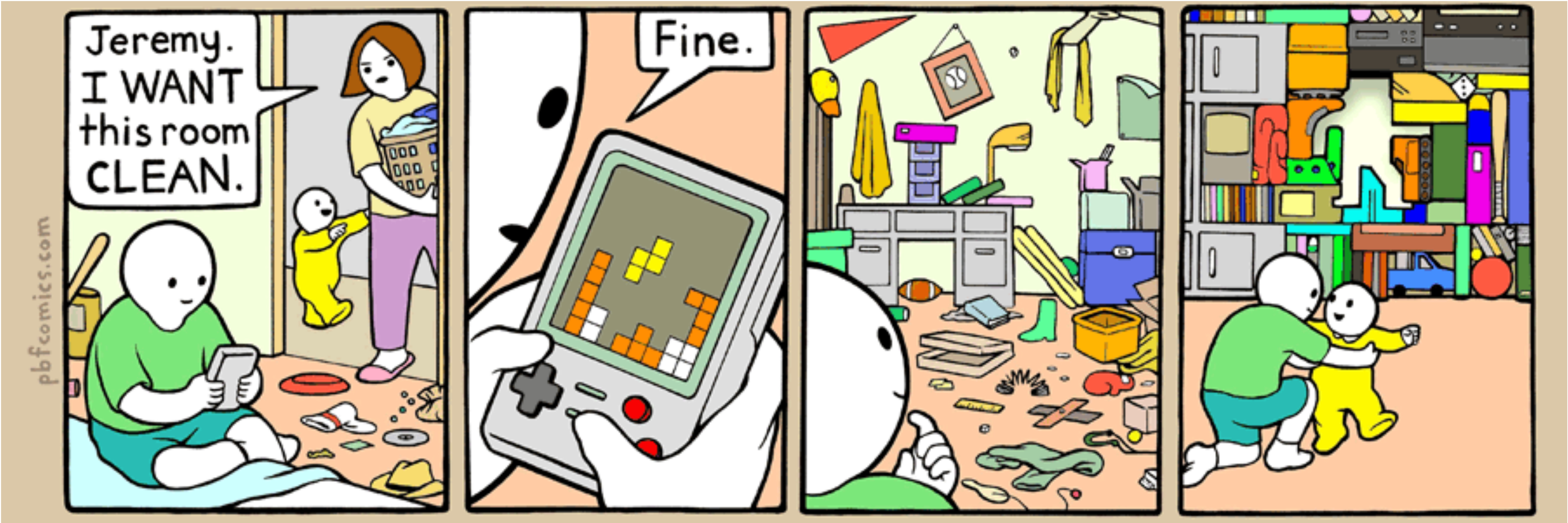
CSCI 333

How Should I Organize My Stuff (Data)?



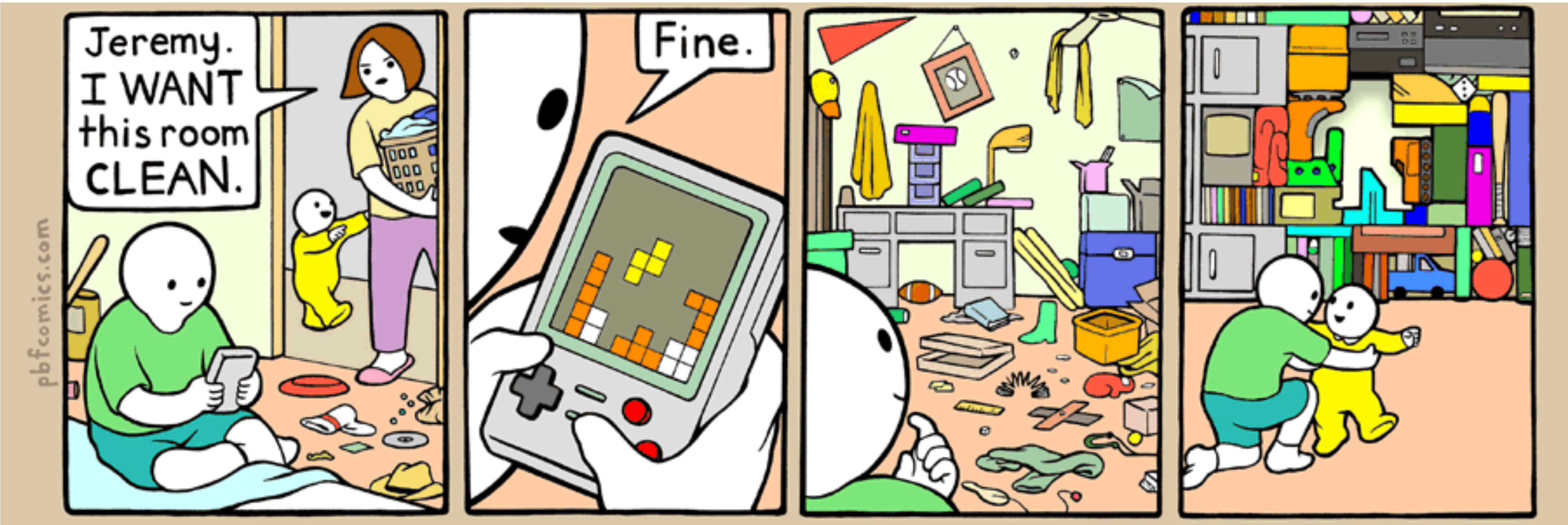
How Should I Organize My Data?

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 (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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Merge

- 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

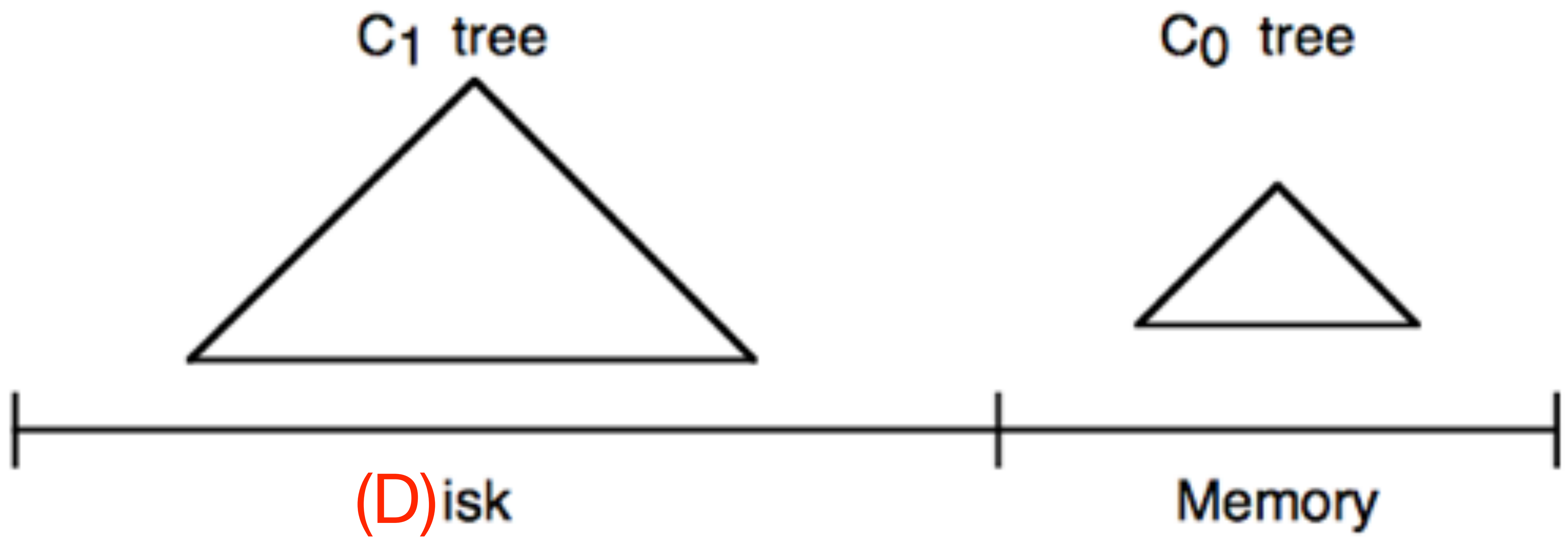


Figure 2.1. Schematic picture of an LSM-tree of two components

[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

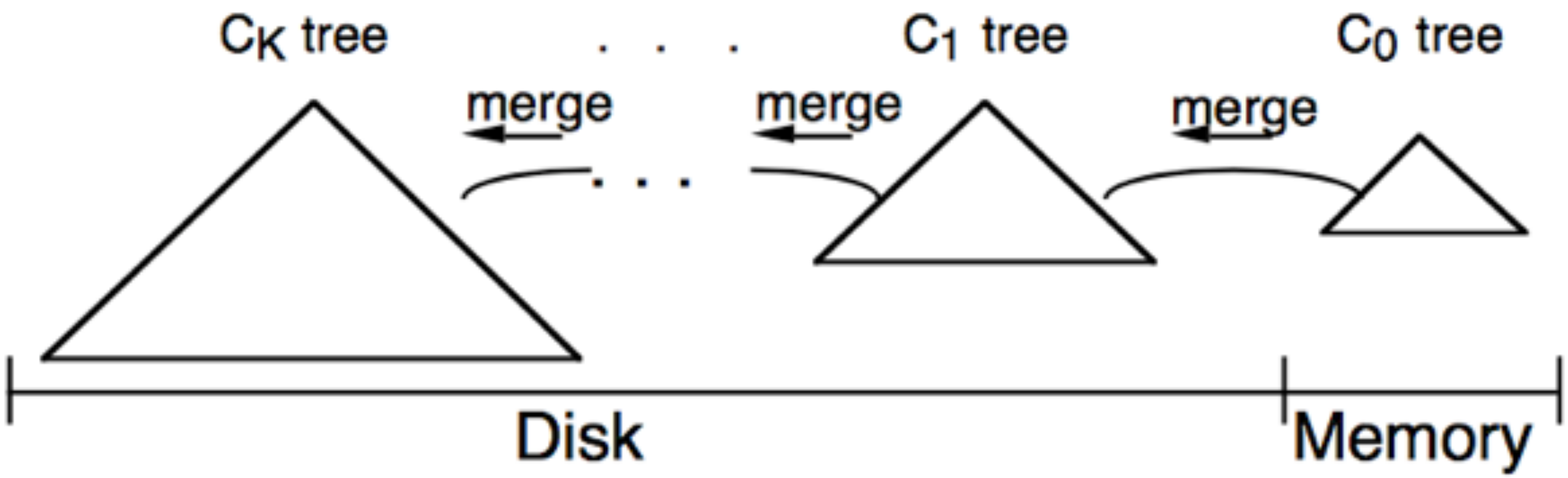


Figure 3.1. An LSM-tree of K+1 components

[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

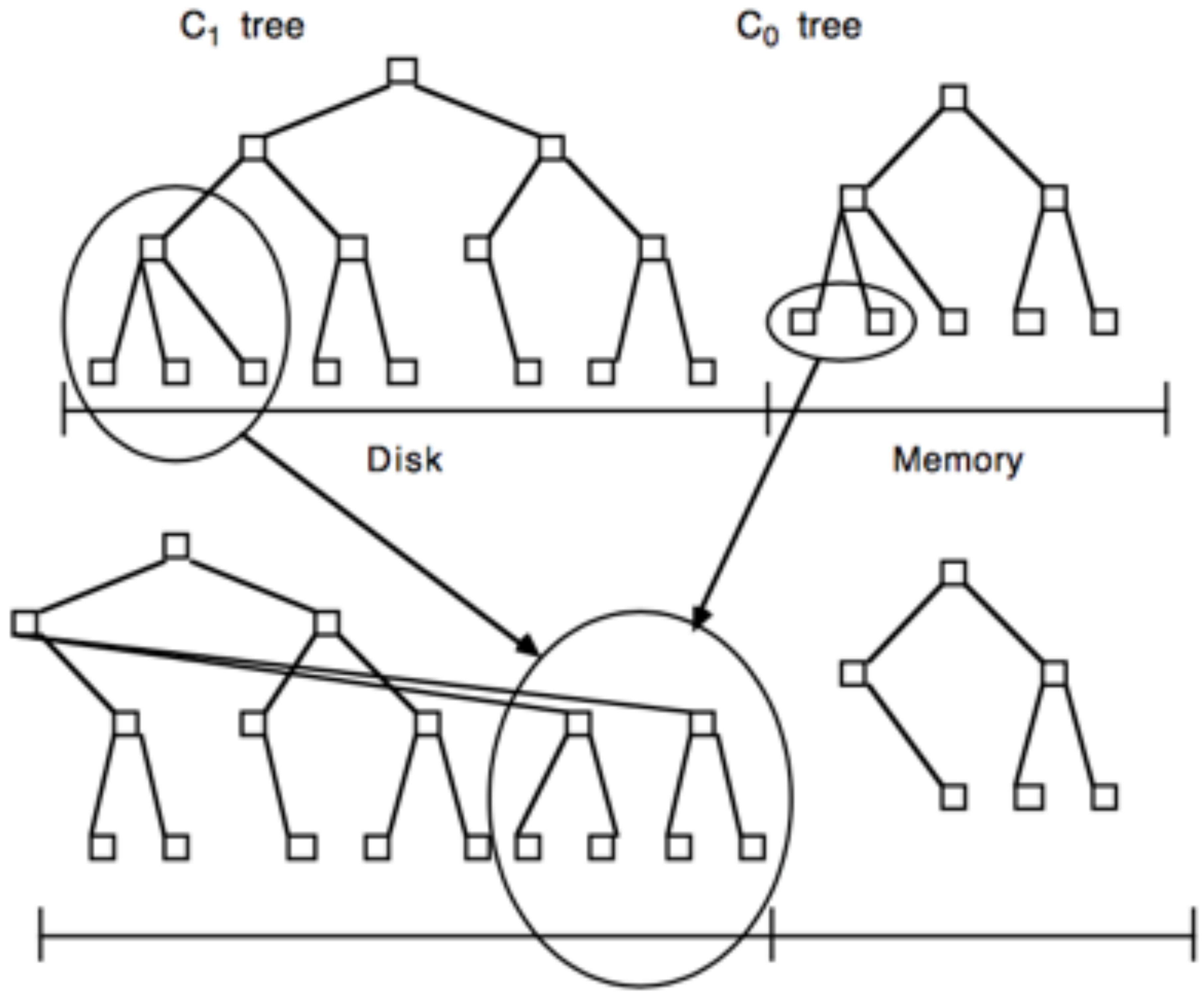


Figure 2.2. Conceptual picture of rolling merge steps, with result written back to disk

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(ki, kl)` - 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^iM

The spine stores metadata about each level

- {**key**$_i$, **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?

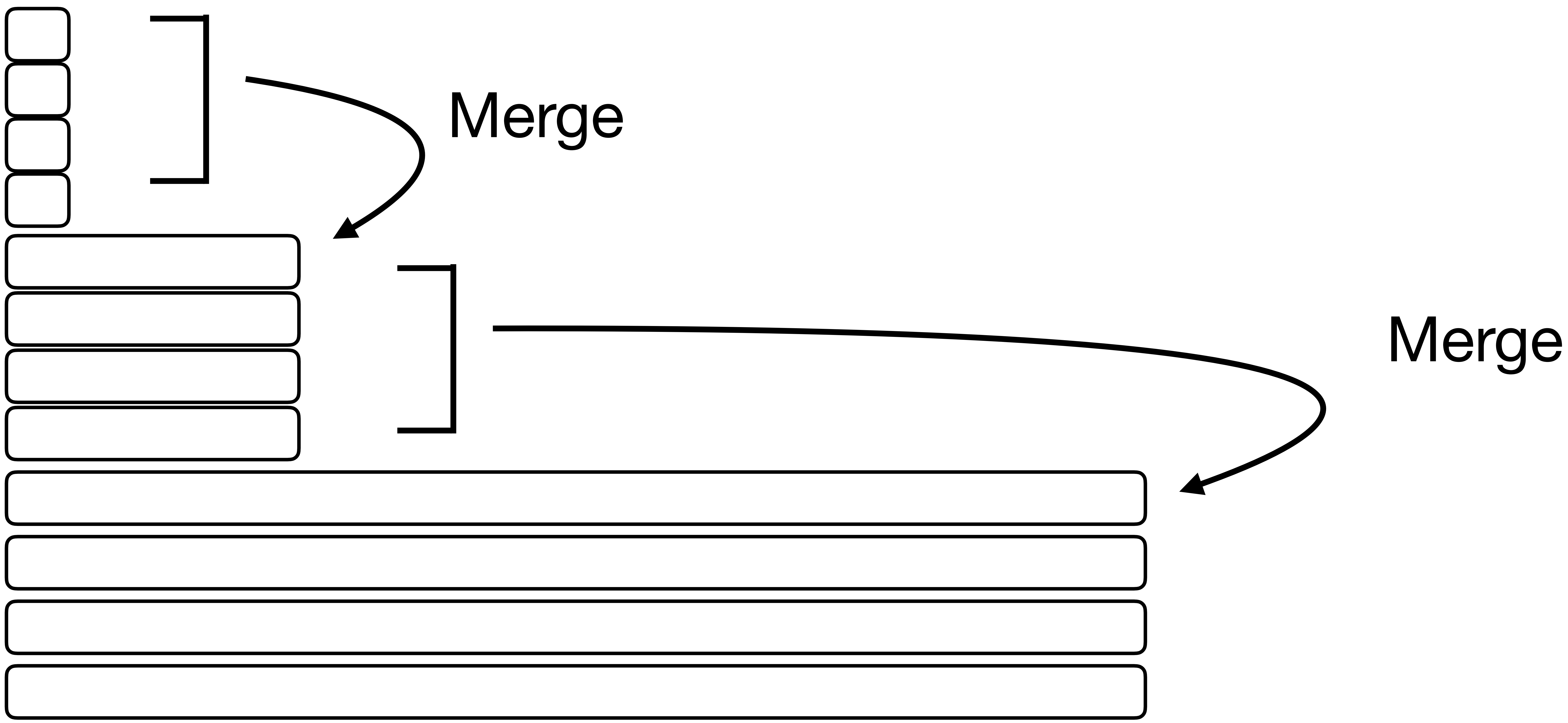
- Ideal data management strategy would:
  - Write all data sequentially for fast inserts
  - Keep all data sorted for fast searches
  - Minimize the number of levels we must search per query (low read amplification)
  - Minimize the number of times we write each key-value pair (low write amplification)

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

Write-optimized Data Structures

Option 1: Size-tiered

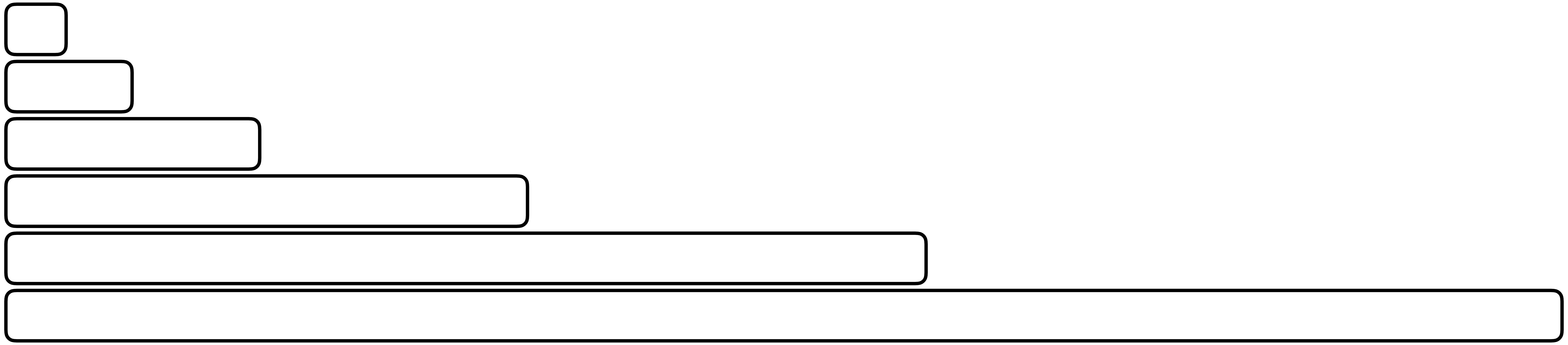
- Each “tier” is a collection SSTables with similar sizes
- When we compact, we merge some number of SSTables with the same size to create an SSTable in the next tier



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 SSTables 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 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

- 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

- 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