# [544] Cassandra Storage Engine

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## Binary Search Trees, B-trees

### **Binary Search Tree**



https://en.wikipedia.org/wiki/Binary\_search\_tree

# 7 16 7 16 1 2 5 6 9 12 18 21

**B-Tree** 

https://en.wikipedia.org/wiki/B-tree

MySQL example: CREATE INDEX Ioan\_amount\_idx USING BTREE ON Ioans(Ioan\_amount)

### **B-Trees:**

- most popular DB index data structure
- fast reads, slower for writes
- more in CS 564

# Log Structured Merge Trees (LSMs)

### Performance:

- faster writes (ALWAYS sequential)
- writes create background work to complete later
- slower reads (for single value, at least)

### Single-node DBs and K/V stores:

- LevelDB
- RocksDB
- SQLite4

### Distributed DBs:

- BigTable
- HBase
- Cassandra

# Outline: Cassandra Storage Engine

### Writing Data: Buffering and Logging

- in general
- Cassandra

Storing Data: SSTables

Reading Data

Compacting Data

writes: block[1] = X, block[4] = B



waiting for the write would be slow: storage is slow in general (these writes would be random)

writes: block[I] = X, block[4] = B



return from write now, buffer work for later...

**writes:** block[1] = X, block[4] = B, block[2] = Y, block[3] = Z



if we're lucky, we'll get more writes that we can do efficiently together



sync to disk eventually

## Crashing at a Bad Time



what will happen to the last written data?

## Solution: Logging Writes

writes: block[0] = W, block[3]=D



sequentially write it to the log now; write to the correct place later

our data is committed once it has been logged

## Crash Recovery



normally a log is never read, just after restarting from a crash

# Durability in a Distributed System

Durability means your data isn't lost when certain bad things happen. Stronger durability means tolerance for more kinds of faults.



what is the least-bad thing that could cause permanent data loss in each scenario?

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each Cassandra table will have its own in-memory memtable

## LSM Buffers: Memtables



occasionally there are multiple memtables for the same table (one can be flushed to disk while another receives new writes)

## Memtables, Memory Layout



remember, JVM memory management is notoriously inneficient and prone to garbage collection pauses

https://www.datastax.com/blog/heap-memtables-cassandra-21

### Memtables, Memory Layout



Cassandra worker: virtual address space

remember, JVM memory management is notoriously inneficient and prone to garbage collection pauses

latest Cassandra versions can store most memtable data off heap

https://www.datastax.com/blog/heap-memtables-cassandra-21



a single log per worker is shared between all tables and written sequentially

keyspaces can be tuned for either performance (log soon) or durability (log before ack) —

CREATE KEYSPACE ???? WITH REPLICATION={...} AND DURABLE\_WRITES=true

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## SSTables (Sorted String Tables)

### Cassandra Worker



it is sorted because Data.db contains key/value pairs sorted by key (which actually is not required to be a string)

### Data.db



## SSTables (Sorted String Tables)

### Cassandra Worker



**problem:** even though Data.db is sorted, we wouldn't want to do binary search on it to find an entry, because the disk I/O would be random

## Index.db



might not have enough RAM to keep all keys in memory, so just points in to the general area rows in this SSTable belonging to the same partition

## SSTables (Sorted String Tables)

### Cassandra Worker



can infer a key must be in the data without actually looking?

Filter.db contains a bloom filter, a very space efficient structure for helping with this. Like Index.db, it is generally loaded to memory.

### Filter.db: bloom filter construction

Step I: compute multiple different hash functions for every key (mod N)

key	hash1(key)%N	hash2(key)%N
А	2	8
В	4	8
•••		



### Filter.db: bloom filter construction

Step I: compute two different hash functions for every key (mod N)



Step 2: flip zeros to ones at each position corresponding to a hashvalue%N

### Filter.db: bloom filter lookup: no case

Was C inserted in the bloom filter?

Assume hash I(C) % N = 2 AND hash2(C) % N = 5



### Filter.db: bloom filter lookup: no case

Was C inserted in the bloom filter?

Assume hash I (C) % N = 2 AND hash2(C) % N = 5



It definitely was NOT inserted. Otherwise we would have flipped position 5 to a one.

### Filter.db: bloom filter lookup: maybe case

Was D inserted in the bloom filter?

Assume hash I(D) % N = 4 AND hash2(D) % N = 8



### Filter.db: bloom filter lookup: maybe case

Was D inserted in the bloom filter?

Assume hash I(D) % N = 4 AND hash2(D) % N = 8



Maybe it was, as both spots are I's. Or it could be a false positive (remember that A and B together flipped these positions).

# **Bloom filters**

### False positive rate depends on

- number of inserts
- number of bits
- number of hash functions

It can be tuned to achieve any desirable rate (but a lower rate means more memory).

# if it were a Python
# data structure:
my\_set = {...} # can add and remove
my\_bloom = ... # can only add

x in my\_set # True or False
x in my\_bloom # Maybe or False (NEVER True)

### https://en.wikipedia.org/wiki/Bloom\_filter



The false positive probability p as a function of number of elements n in the filter and the filter size m. An optimal number of hash functions  $k = (m/n) \ln 2$  has been assumed.

## TopHat

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### Example: lookup value for K









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- merge sort
- performance considerations
- HBase vs. Cassadra

# Controlling Read Cost

Only dumping out large, immutable SSTables is good for writes (everything is sequential).

Over time, read cost grows with number of SSTables.

### Bloom filters help, but have limitations:

- false positives
- same key might be any many SSTables
- sometimes want to read values between K1 and K2 (a "range query") instead of for a single K value (a "point lookup")

We can reduce the number SSTables by "merge sorting" multiple small ones into one bigger one. This is called "compaction".

## **Compaction: Merge Sorting SSTables**



this example has two input SSTables, but it could be more

#### newer

key	value
А	(1,4)
 G	(8,9)
 Μ	tombstone

### older

key	value
С	(9,3)
D	(2,8)
G	(5,4)
М	(3,4)
Q	(2,4)

### compacted

key	value

#### newer

 key	value
A	(1,4)
G	(8,9)
Μ	tombstone

### older

key	value
С	(9,3)
D	(2,8)
G	(5,4)
М	(3,4)
Q	(2,4)

### compacted

key	value
А	(1,4)

#### newer

 key	value
А	(1,4)
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### older

_	key	value
	С	(9,3)
	D	(2,8)
	G	(5,4)
	Μ	(3,4)
	Q	(2,4)

### compacted

key	value
Α	(1,4)
С	(9,3)
D	(2,8)

### if both have same value, use newer

#### newer

÷

kev	value	key	value
Α	(1.4)	Α	(1,4)
G	(8,9)	С	(9,3)
M	tombstone	D	(2,8)
		G	(8,9)
0	lder		
key	value		

key	value
С	(9,3)
D	(2,8)
G	(5,4)
M	(3,4)
Q	(2,4)

do we write a new tombstone, or delete the entry?

the key might appear in even older SSTables: write tombstone

the key cannot appear in older SSTables: delete it

newer

### compacted

ne			_
key	value	key	value
A	(1,4)	A	(1,4)
G	(8,9)	C	(9,3)
M	tombstone	D	(2,8)
	•	G	(8,9)
o	der	M	tombstone
key	value		
С	(9,3)	once we get to the end of one input we just work from the others	
D	(2,8)		
G	(5,4)		
Μ	(3,4)		
Q	(2,4)		



### compacted

key	value
Α	(1,4)
С	(9,3)
D	(2,8)
G	(8,9)
М	tombstone
Q	(2,4)

delete old SSTables

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### Write Overheads

Compactions make reads faster, but create write overheads.

Most written data gets re-written many times after the initial write (this is called "write amplification").

For example, in Facebook messages on HBase: "Compaction causes about 17x more writes than flushing does, indicating that a typical piece of data is relocated 17 times." ~ Analysis of HDFS Under HBase: A Facebook Messages Case Study, Harter et al.

## Background vs. Foreground Work

Compaction is background work, making LSM-based storage systems ideal for "bursty" workloads:



# **Compaction Policies**

### SizeTieredCompactionStrategy

- optimized for write-heavy workloads
- try to compact SSTables of similar size together
- merge sorting very small files with very large is inneficient
- DEFAULT

### LeveledCompactionStrategy

- optimized for read-heavy workloads
- SSTables are assigned levels
- A key can appear in at most SSTable per level (except level 0)

There are other strategies not covered in 544...

### **Compaction Policies**



Say you want to read key C, but an SSTable's first key is E and last is Y. You can safely ignore that SSTable.

# Reading a Key



leveled approach can avoid most SSTables during read

## Compacting SSTables

### WINNER



size-tiered can compact similarly sized SSTables together (more efficient than compacting very small files with very large files)

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### HBase vs. Cassandra



### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



note: this shows all 3 Cassandra LSMs in the same state, but they don't need to be in sync.

### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



compute: HBase merges Ix, Cassandra merges 3x. Winner: HBase

HBase

### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



disk reads: HBase uses ???? MB, Cassandra uses ???? MB. Winner: ????

### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



disk reads: HBase uses 2 MB, Cassandra uses 6 MB. Winner: HBase

### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



disk writes: HBase uses ???? MB, Cassandra uses ???? MB. Winner: ????

### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



disk writes: HBase uses 6 MB, Cassandra uses 6 MB. Winner: Tie

### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



network I/O: HBase uses ???? MB, Cassandra uses ???? MB. Winner: ????

### Scenario: compact TI and T2 (both I MB) to produce T3 (2 MB)



network I/O: HBase uses 4-8 MB, Cassandra uses 0 MB. Winner: Cassandra

### Architecture: HBase vs. Cassandra

### HBase

LSM

Replication

- disk read efficient
- compute efficient

Cassandra

Replication

LSM

- network efficient
- flexible (different nodes can compact differently)