A Comparative Study of Secondary Indexing Techniques in LSM-based NoSQL Databases

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ABSTRACT

NoSQL databases are increasingly used in big data applications, because they achieve fast write throughput and fast lookups on the primary key. Many of these applications also require queries on non-primary attributes. For that reason, several NoSQL databases have added support for secondary indexes. However, these works are fragmented, as each system generally supports one type of secondary index, and may be using different names or no name at all to refer to such indexes. As there is no single system that supports all types of secondary indexes, no experimental head-to-head comparison or performance analysis of the various secondary indexing techniques in terms of throughput and space exists. In this paper, we present a taxonomy of NoSQL secondary indexes, broadly split into two classes: *Embedded Indexes* (i.e. lightweight filters embedded inside the primary table) and *Stand-Alone Indexes* (i.e. separate data structures). To ensure the fairness of our comparative study, we built a system, *LevelDB++*, on top of Google's popular open-source LevelDB key-value store. There, we implemented two Embedded Indexes and three state-of-the-art Stand-Alone indexes, which cover most of the popular NoSQL databases. Our comprehensive experimental study and theoretical evaluation show that none of these indexing techniques dominate the others: the embedded indexes offer superior write throughput and are more space efficient, whereas the stand-alone secondary indexes achieve faster query response times. Thus, the optimal choice of secondary index depends on the application workload. This paper provides an empirical guideline for choosing secondary indexes.

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1 INTRODUCTION

In the age of big data, more and more services are required to ingest high volume, velocity and variety data, such as social networking data, smartphone apps usage data and click through data. NoSQL databases were developed as a more scalable and flexible alternative to relational databases. NoSQL databases, such as HBase [13], Cassandra [31], Voldemort [12], MongoDB [26], AsterixDB [2] and LevelDB [23] to name a few, have attracted huge attention from industry and research communities, and are widely used in products. Through the use of Log-Structured Merge-Tree (LSM) [34], NoSQL systems are particularly good at supporting two capabilities: (a) fast write throughput, and (b) fast lookups on the primary key of a data entry (See Appendix A.1 for details on LSM storage framework). However, many applications also require queries on non-key attributes which is a functionality commonly supported in RDBMSs. For instance, if a tweet has attributes such as tweet id, user id and text, then it would be useful to be able to return all (or the most recent) tweets of a user. However, supporting secondary indexes in NoSQL databases is challenging, because secondary indexing structures must be maintained during writes, while also managing the consistency between secondary indexes and data tables. This significantly slows down writes, and thus hurts the system's capability to handle high write throughput which is one of the most important reasons why NoSQL databases are used.

Table 1 shows the operations that we want to support. The first three operations (GET, PUT and DEL) are already supported by existing NoSQL stores like LevelDB. Note that the secondary attributes and their values are stored inside the value of an entry, which may be in JSON format: $v = \{A_1 : val(A_1), \cdots, A_l : val(A_l)\}$, where $val(A_i)$ is the value for the secondary attribute A_i. For example, the key of a tweet entry could be $k = tweet\ id$, $A_1 = user\ id$ and $A_2 = body\ text$. Key k should not be confused with limit K (top-K), which means K most recent records in terms of insertion time in the database.

Table 1: Set of operations in a NoSQL database.

Operation	Description
GET (k)	Retrieve value identified by primary key k.
PUT (k, v)	Write a new entry $\langle k, v \rangle$ (or overwrite if k already exists), where k is the primary key.
DEL (k)	Delete the entry identified by primary key k if any.
LOOKUP (A, a, K)	Retrieve the K most recent entries with $val(A) = a$.
RANGELOOKUP (A, a, b, K)	Retrieve the K most recent entries with $a \leq val(A) \leq b$.

Stand-Alone Secondary Indexes. Current NoSQL systems have adopted different strategies to support secondary indexes (e.g., on the user id of a tweet). Most of them maintain a separate Stand-Alone Index table. For instance, MongoDB [26] uses B+-tree for secondary index, which follows the same way of maintaining secondary indexes as traditional RDBMSs. They perform in-place updates (which we refer as "Eager" updates, and we refer to such indexes as Eager Indexes) of the B+ tree secondary index, that is, for each write in the data table the index (e.g., B+ tree) is updated. In the case of some LSM-based NoSQL systems (e.g., BigTable [5]),

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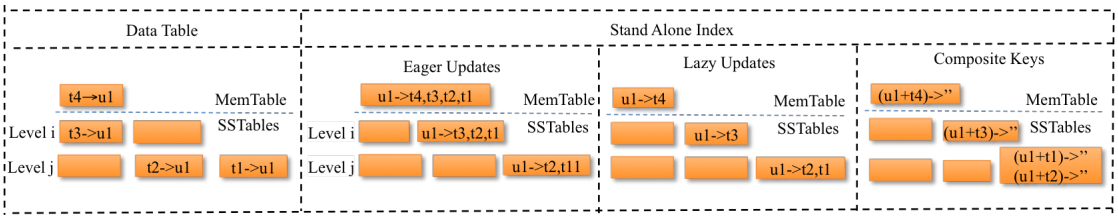
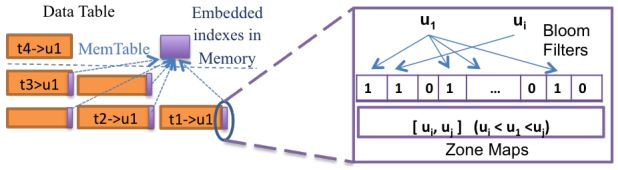


(a) Comparison between Eager and Lazy updates, and <secondary+primary> Composite keys in Stand-Alone Indexes



(b) Zone maps and bloom filters in Embedded Index

Figure 1: Comparison between various secondary indexes after operations in Example 1. We use the notation $key \rightarrow value$.

which store a secondary index as an LSM table (column family), an Eager update is technically not in-place, but a new posting list is written that invalidates the older ones. In contrast to in-place updates, other LSM-based systems (e.g., Cassandra [31]) perform append-only updates on the LSM index table, which we refer as "Lazy" updates, and Lazy Indexes.

Example 1. *Consider the current state of a database right after the following sequence of operations* PUT(t1, {u1, text1}),PUT(t2, {u1, text2}),PUT(t3, {u1, text3},$\cdots$), *where ti is a tweet id, ui is a user id, and texti is the text of a tweet. Then, as shown in Figure 1(a), to execute* PUT(t4, {u1, text4}) *on an Eager Index, we must retrieve the list for u1, add t4 and save it back, whereas for a Lazy Index, we simply issue a* PUT(u1, {t4}) *on the user id index table without retrieving the existing posting list for u1. The old postings list of u1 is merged with* (u1, {t4}) *later, during the periodic compaction phase.*

A drawback of the lazy update strategy is that reads on index tables become slower, because they have to merge the posting lists at query time. Earlier versions of Cassandra handled this by first accessing the index table to retrieve the existing posting list of u1, then writing back a merged posting list to the index table. Then the old posting list becomes obsolete. However, this Eager Index degrades the write performance.

In addition to these Stand-Alone indexes which maintain posting lists, several systems (e.g. AsterixDB [2], Spanner [7]) adopt a different approach to maintain the secondary indexes, which we refer as Composite Index. Here, each entry in the secondary indexes is a composite key consisting of (secondary key + primary key). The secondary lookup is a prefix search on secondary key, which can be implemented using regular range search on the index table. Here, writes and compactions are faster than "Lazy," but secondary attribute lookup may be slower as it needs to perform a range scan on the index table. We have implemented Eager, Lazy and Composite Stand-Alone Indexes. All these indexes can naturally support both lookup and range queries.

Embedded Secondary Indexes. We also built *Embedded indexes*, which differ in that there is no separate secondary index structure, but secondary attribute information is stored inside the original (primary) data blocks. We built two Embedded Indexes. The first is based on *bloom filters* [4], which are a popular hashing technique for set membership check (See Appendix A.3 for details on bloom filters). Bloom filters are already being used for primary indexing in many systems such as BigTable[5], LevelDB[23] and AsterxiDB[2]. But surprisingly, to our best knowledge, it has not been used for secondary attribute lookup in any of the existing NoSQL system. A drawback of bloom filter index is that it can only support lookup queries.

In addition to bloom filters, we also implement another Embedded Index, *zone maps*, which typically store the minimum and maximum values of a column (attribute) in a table per disk block. Zone maps are used in Oracle [27], Netezza [25], and AsterixDB [2]. Zone maps can be used for both lookup and range queries. However, in practice, zone maps are only useful when the incoming data is *time-correlated*, otherwise most of the data blocks have to be examined [2]. An attribute is called time-correlated if its value for a record is highly correlated with the record's insertion timestamp. For example, tweet-id is time-correlated because the tweet-id value increases with time. Note that the higher the correlation the stronger pruning we achieve in zone maps. No index's or algorithm's correctness requires that an attribute is time-correlated.

Note that these Embedded Indexes do not create any specialized index structure, but instead attach a memory-resident bloom filter signature and a zone map to each data block for each indexed secondary attribute. As LSM files on disks (called SSTables, see Appendix A.2) are immutable, these filters do not need to be updated; they are naturally computed when an SSTable is created. *In our experiments, we consider both bloom filters and zone maps together as one index, which we refer as Embedded Index.*

Example 1 (cont'd) *Figure 1 shows the differences between the five indexing strategies. As in LSM-style storage structures, data are organized as levels, three levels shown in Figure 1, where the top row is in-memory and the bottom two on disk. Lower levels are generally larger and store older data. In some systems like LevelDB, lower levels*

have more SSTables of the same size, and in some like AsterixDB, lower levels have just one but larger SSTable. Each orange rectangle in Figure 1 represents a data file (SSTable).

Table 2 shows the various secondary indexing techniques used by existing NoSQL systems, and by our LevelDB++. As we see, each system only implements one or two of these approaches, which does not allow a fair comparison among them, which is a key contribution of this paper. More details on how different systems adopt these techniques are described in Section 2.

Summary of Methodology. To compare different indexing techniques, we implemented all of them on top of LevelDB [23] framework, which to date does not offer secondary indexing support. We chose LevelDB over other candidates, such as RocksDB [20], because it is a single-threaded pure single-node key value store, so we can easily isolate and explain the performance differences of the various indexing methods. We compare these algorithms using multiple metrics including size, throughput, number of random disk accesses and scalability. We ran experiments using several static workloads (i.e. build the index first and perform reads later) and dynamic (mix of reads, writes, updates) workloads, using real and synthetic datasets. We measured the response time for queries on non-primary key attributes, for varying top-K and selectivity.

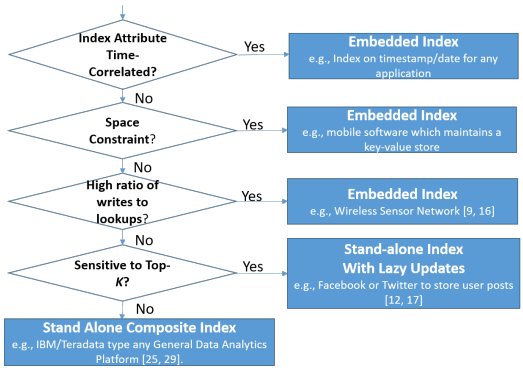


Figure 2: Proposed secondary index selection strategy.

Summary of Results. As shown in Figure 2, the Embedded Index has lower maintenance cost in terms of time and space compared to Stand-Alone Indexes, but Stand-Alone Indexes have faster query (LOOKUP and RANGELOOKUP) times. Embedded Index is a better choice in the cases when index attribute is time-correlated (zone maps perform well) or when space is a concern, (e.g., to create a local key-value store on a mobile device) or if the query workload contains relatively small (< 5%) ratio of LOOKUP/RANGELOOKUP queries over GETs and is heavy on writes (> 50% of all operations). An example of such an application is wireless sensor networks where a sensor generates data of the form (measurement id, temperature, humidity) and needs support for secondary attribute queries [8, 15]. In terms of implementation, the Embedded Index is also easier to be adopted, as the original basic operations (GET, PUT and DEL) on the primary key remain unchanged. The Embedded Index also simplifies the consistency management during secondary lookups, as we do not have to synchronize separate data structures. Among the Stand-Alone Indexes, Lazy Index achieves overall better performance for smaller top-K LOOKUPs and RANGELOOKUPs. For instances, it is reported that there are much more reads than writes in Facebook and Twitter [11, 16], and hence an ideal index to store user posts which is sensitive to top-K, will be Lazy Index. Eager Index shows exponential write costs and is not suitable for any workloads. Composite Index outperforms Lazy Index when there is no limit on top-K. For example, Composite Index is a good solution for general analytics platforms (e.g. IBM [24], TeraData [28]) where one may group by year or department and so on.

Summary of Contributions. We make the following contributions:

- We perform an extensive study on the state-of-the-art secondary indexing techniques for NoSQL databases and present a taxonomy of NoSQL secondary.
- We implement two Embedded Indexes (Bloom filters and Zone maps) on LSM-based stores to support secondary lookups and range queries, and theoretically analyze their cost.
- We implement Lazy, Eager and Composite Stand-Alone Indexes on LSM-based stores and optimize each index for a fair comparison. We also theoretically analyze their cost.
- We conduct extensive experiments on LevelDB++ to study the trade-offs between different indexing techniques on various workloads (Section 5).
- We published the LevelDB++ code base as open-source, which includes our secondary indexes implementation on top of LevelDB, along with a Twitter-based data generator [30].

The rest of the paper is organized as follows. Section 2 reviews the related work. Sections 3 and 4 describe the indexing techniques and their theoretical cost models. Section 5 presents the experimental evaluation and we conclude in Section 6.

2 RELATED WORK

The idea of having the secondary index organized as a table has been studied in the past (e.g. Yahoo PNUTS [1]). Cassandra [31] supports secondary indexes by populating a separate table (column family in Cassandra's terminology) to store the secondary index for each indexed attribute. Their index update closely follows our Lazy Index approach. AsterixDB [2] introduces a framework to convert an in-place update index like B+ tree and R-tree to an LSM-style index, in order to efficiently handle high throughput workloads. Their secondary indexes closely follow our Composite Index strategy. This can be viewed as complementary to our work as we work directly on LSM-friendly indexes (set of keys with flat postings lists). AsterixDB also adopts zone maps to prune disk components (i.e. SSTables) for secondary lookups. But their zone maps are limited as they are only min-max range filters of whole SSTable files whereas our zone maps also maintain filters for all blocks inside an SSTable. Secondary indexes on HBase are discussed in [36], although that paper's focus is on consistency levels. Document-oriented NoSQL databases like CouchDB [19] and MongoDB [26], similarly to RDBMs, employ B+-trees to support secondary indexes. They mostly perform in-place update on the secondary index similarly to our Eager Index. A variation of Lazy Index is implemented in DualDB [35], although it is used as primary index and customized for pub/sub features only. HyperDex [10] proposes a distributed key-value store supporting search on secondary attributes. They partition the data across the cluster

Table 2: Different Secondary Indexing techniques supported in different NoSQL databases

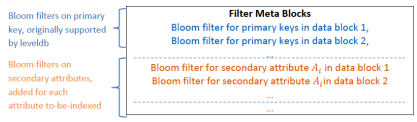
NoSQL Storage Systems	Embedded Index		Stand Alone Index		
	Zone Map Index	Bloom Filter Index	Lazy Index	Eager Index	Composite Index
LevelDB++	✓	✓	✓	✓	✓
LevelDB [23], RocksDB [20]					
Cassandra [31]			✓		
AsterixDB [2], Spanner [7]	✓				✓
MongoDB [26], CouchDB [19], DynamoDB [18], Riak [3], Aerospike [17]				✓	
Oracle [27], Netezza [25]	✓				

by taking the secondary attribute values into consideration. Each attribute is viewed as a dimension (e.g., a tweet may have two dimension tweet id and user id), and each server takes charge of a "subspace" of entries (e.g., any tweet with tweet id in [tid1, tid2] and user id in [uid1, uid2]). Innesto [33] applies a similar idea of partitioning and adds ACID properties in a distributed key-value store. DynamoDB [18], a distributed NoSQL database service, supports both global and local secondary indexes with a separate index table similar to Stand-Alone Indexing. Riak [3], similarly supports secondary indexing by means of Stand-Alone Index table for each partition, and performs an Eager update after each write operation. In this paper, our focus is on a single-machine storage engine for NoSQL databases. The distribution techniques of HyperDex, DynamoDB, Riak and Innesto can be viewed as complementary if we want to move to a distributed setting.

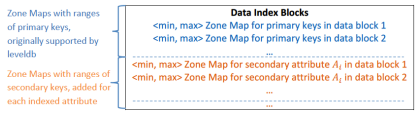
3 EMBEDDED INDEX

Overview. As shown in Figure 1(b), in each SSTable file we constructed a block with a set of bloom filters on the secondary attributes and appended the bloom filter block to the end of the SSTable. Specifically, a bloom filter bit-string was stored for each secondary attribute for each block inside the SSTable file (recall that an SSTable file is partitioned into blocks, see Appendix A.1 and A.2 for a detailed overview of the LSM storage model and LevelDB storage architecture). In addition, we added zone map indexes for accelerating range lookup on secondary keys. These zone maps store the minimum and maximum range of secondary keys for each data block. We used these zone maps to further accelerate point lookup queries. We generally compute these bloom filters and zone maps for each block when a new SSTable is created (i.e. an LSM memory component MemTable is flushed to disk or a compaction creates new SSTables). Note that these bloom filters and zone maps are loaded in memory (the same approach is used currently with the bloom filters of the primary key in systems like Cassandra and LevelDB). Hence, the scan over the disk files is converted to a scan over in-memory bloom filters/zone maps. We only access the disk blocks, which the bloom filter returns as positive. We refer to these indexes as *Embedded Index*, as no separate data files are created. Instead, the bloom filters and zone maps are embedded inside the main data files.

LevelDB, as other NoSQL databases like Cassandra, already employs bloom filters and zone maps to accelerate reads on primary keys. Several types of meta blocks are already supported in LevelDB (see Appendix A.2). We modify the filter meta block and the data index block to add secondary attribute bloom filters and zone maps, as shown in Figure 3. For lookup in the MemTable, we maintain an in-memory B-tree on the secondary attribute(s). We also store one zone map for each SSTable file, in a global metadata file, allowing us to access the min-max range of secondary keys in the whole file, to avoid searching in block-level zone maps.



(a) Bloom filters



(b) Zone maps

Figure 3: Modified LevelDB SSTable for Embedded Index.

LOOKUP(A_i, a, K). We scan one level at a time until K results have been found. A key challenge is that within the same level there may be several entries with the queried secondary attribute value $val(A_i) = a$, and these entries are not stored as ordered by time (but by primary key). Fortunately, LevelDB, as other NoSQL systems, assigns an auto-increment sequence number to each entry at insertion, which we use to perform time ordering within a level. Hence, we must always scan until the end of a level before termination. During this scan, we use the bloom filter and zone map indexes to check each data block in the SSTables. If both index checks return true, we read a block from disk.

To efficiently compute the top-K entries, we maintain a min-heap ordered by the sequence number. If we find a match (i.e. we find a record that has secondary attribute value $val(A_i) = a$), then if the heap size is equal to K, we first check whether it is an older record than the root of the min-heap. If it is a newer match or the heap size is less than K, then we check whether it is a valid record (i.e. whether it is invalidated by a new record in the data table). We check this by issuing a special function *GetLite(k, currentlevel)* (Algorithm 5 in Appendix), which is a variation of the *GET* operation. Note that here we know the *currentlevel* (i.e. the level where the key is placed) of the actual record. GETLite checks the in-memory metadata, index block and bloom filters for primary keys to check which level contains the key. If the key appears in the upper levels (0 to $currentlevel - 1$), that means there is an updated version of the key that is present in the database and this record is considered invalid. Here, we do not need to perform disk I/O, which a regular *GET* operation would do. This simple optimization in Embedded Index significantly reduces disk I/O.

RANGELOOKUP(A_i, a,b, K). We support RANGELOOKUP in Embedded Index via zone maps. Similar to LOOKUPs, here we check SSTables level by level. First, we check the global zone map of an SSTable to check if we can avoid scanning this file. Then we check the zone maps of each block of the SSTable to find overlaps with the query range $[a, b]$ and find out which blocks may contain records with the secondary attribute value a. A min-heap is similarly used here to maintain top-K and we stop scanning after reaching to the end of one level if K matches are found. The pseudocode of LOOKUP (Algorithm 5) and RANGELOOKUP (Algorithm 8) on Embedded Index is presented in Appendix B.

GET, PUT and DEL. A key advantage of the Embedded Index is that only small changes are required for all three interfaces: GET(k), PUT(k, v), and DEL(k). Obviously, GET(k) needs no change as it is a read operation and we have only added bloom filter and zone map index to the data files. As SSTables are immutable, PUT and DEL just updates the in-memory B-tree for the MemTable data.

3.1 Cost Analysis

Cost of GET/PUT/DEL queries. The Embedded Index does not incur much overhead on these operations. MemTable does not have bloom filters or zone maps, so there is no extra cost in maintaining them for each operation. It only adds small in-memory overhead on the compaction process to build bloom filters and zone maps for each indexed attribute per block and small overhead for updating the B-tree for MemTable.

Cost of LOOKUP and RANGELOOKUP queries. Let the number of blocks in level-0 be b (and thus level-i has approximately $b \cdot 10^i$ blocks). According to Equation 1, the expected minimal false positive rate of the bloom filter is $2^{-\frac{m}{S} ln2}$, denoted as fp (for more details on bloom filters, see Appendix A.3). Thus the approximate number of block accesses on level-i for LOOKUP due to false positives is $fp \cdot b \cdot 10^i$. Hence, if a LOOKUP query needs to search on L levels, the expected block accesses are $\sum_{i=0}^{L} \left(fp \cdot b \cdot 10^i\right) = \frac{fp \cdot b \cdot (10^{L+1}-1)}{9}$. Let us assume that matched entries are found in $K + \epsilon$ blocks, then the total number of block accesses is $K + \epsilon + \frac{fp \cdot b \cdot (10^{L+1}-1)}{9}$. Here ϵ represents the extra cost of searching to the end of a level to find top-K from matched entries. Note that, the CPU cost of computing membership check using in-memory bloom filters cannot be neglected here. For example, if the database size is 100GB and block size is 4KB, that means there exist 25 million bloom filters for one secondary indexes and a LOOKUP query may need to check all of them in the worst case. The CPU cost is generally much smaller for an index on a time-correlated attribute, because file-level zone maps are very effective and prune most files.

For RANGELOOKUP operation, the false positive rate depends on the distribution of the secondary key ranges in different blocks. In the worst case for non time-correlated index, RANGELOOKUP may have to traverse all blocks in the database, same as if there is no index. For time-correlated index, the worst case cost is $K + \epsilon$ block accesses.

The worst-case number of disk accesses for different operations in Embedded Index is presented in Table 3. The Embedded Index will achieve better LOOKUP query performance on low cardinality data (i.e., an attribute has small number of unique attribute values), because fewer levels must be accessed to retrieve K matches.

Table 3: Disk accesses for operations in Embedded Index. (means that CPU cost may not be ignored)**

Operation	Read I/O	Write I/O
GET(k)	1	0
DEL(k), PUT(k, v)	0	1
LOOKUP	$(K + \epsilon) + \frac{fp \cdot b \cdot \left(10^{L+1}-1\right)}{9}$ **	0
RANGELOOKUP	$(K + \epsilon)$ (Time-correlated index attribute), Same as no index (non time-correlated)	0

4 STAND-ALONE INDEX

4.1 Stand-Alone Index with Posting Lists

A Stand-Alone secondary index in a NoSQL store can be logically created as follows. For each indexed attribute A_i, we build an index table T_i, which stores the mapping from each attribute value to a list of primary keys, similarly to an inverted index in Information Retrieval. That is, for each key-value pair $\langle k, v \rangle$ in the data table with $val(A_i)$ not null, k is added to the postings list of $val(A_i)$ in T_i. Posting lists can be serialized as a single JSON array. Example 2 presents an illustration for this.

Example 2. *Assume the current state of a database right after the following sequence of operations* PUT(t1, {u1, text1}),...,PUT(t2, {u1, text2}),...,PUT(t3, {u2, text3}), PUT(t4, {u2, text4}). *Tables 4a and 4b show the logic presentation of the state of primary data table(*UserIndex*) and secondary Stand-Alone Index(*TweetData *) in a key-value store after these four operations.*

Table 4: Stand-Alone UserIndex with Posting lists of tweets

(a) TweetsData - **Primary table**

Key	Value
t1	{"UserID": u1, "text": "t1 text"}
t2	{"UserID": u1, "text": "t2 text"}
t3	{"UserID": u2, "text": "t3 text"}
t4	{"UserID": u2, "text": "t4 text"}

(b) UserIndex

Key	Value
u1	[t2, t1]
u2	[t4, t3]

Compared to the Embedded Index, Stand-Alone Index has overall better LOOKUP performance, because it can get all candidate primary keys with one read in the index table in Eager Index (or up to L reads when there are L levels in the case of Lazy Index as we discuss below). However, Stand-Alone Index is more costly due to the maintenance of index table upon writes (PUT(k, v) and DEL(k)) in the data table in order to keep the consistency between them. We present two options to maintain the consistency between data and index tables, Eager updates and Lazy updates, discussed in Sections 4.1.1 and 4.1.2 respectively. We have implemented both options on LevelDB.

4.1.1 Eager Index. PUT(k, $\{A_i : a_i\}$)/DEL(k): Upon a PUT, a Stand-Alone Index with Eager updates (i.e. Eager Index) first reads the current postings list of a_i from the index table, adds k to the list and writes back the updated list. *This means that, in contrast to the Lazy Index, only the highest-level posting list of a_i needs to be retrieved, as all the lower ones are obsolete.*

Example 3. *Suppose PUT(t3, {"UserID": u1, "Text": "t1 text"}) is issued after operations in example 2, which updates the UserID attribute of t3 from u2 to u1.*

Figure 4 depicts a possible initial and final instance of the LSM tree for Eager Index after PUT operation in Example 3. The DEL(k) operation in Eager Index follows the same read-update-write process to update the list. Note that the compaction on the index tables

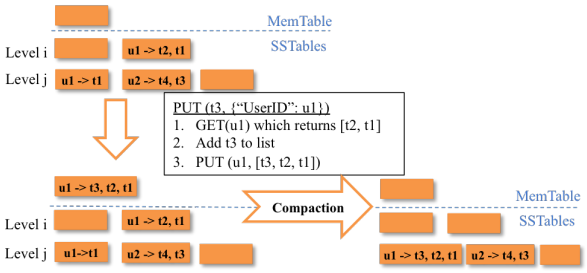


Figure 4: Stand-Alone Eager Index and its compaction.

works the same as the compaction on the data tables.

LOOKUP(A_i, a, K): A key advantage of Eager Index is that LOOKUP only needs to read the postings list of a in the highest level in T_i. To support top-K LOOKUPs, we maintain the postings lists ordered by time (sequence number) and then only read a K prefix of them. For each entry k in the list of primary keys, we issue a GET(k) on data table to retrieve the data record. We make sure $val(A_i) = a$ for each entry to check the validity as there could be invalid keys in the postings list of a caused by updates on the data table (i.e. Insertion of an existing key with a different secondary key). Pseudocode of LOOKUP (Algorithm 2) on Eager Index is presented in Appendix B.

RANGELOOKUP(A_i, a, b, K): To support range query (RANGELOOKUP) on secondary attribute in Eager Index, we use range query API in LevelDB on primary key. We issue this range query on our index table for given range $[a, b]$. For each match x, we retrieve K number of most recent primary keys from the posting list which is already sorted by time. To return a top-K among different secondary keys in range $[a, b]$, we need to add associated posting lists' primary keys to the min-heap to get the top-K. To sort mean-heap by timestamps, we attach a sequence number to each entry in the postings list on every write. This sequence number represents entry time for each entry in the posting lists.

4.1.2 Lazy Index. PUT(k, $\{A_i : a_i\}$)/DEL(k): The Eager Index still requires a read operation to update the index table for each PUT, which significantly slows down PUTs. In contrast, the Lazy Index works as follows. Upon PUT (on the data table), it just issues a PUT($a_i, [k]$) to the index table T_i but nothing else. Thus, the postings list for a_i will be scattered in different levels. During merge compaction, we merge these fragmented lists. DEL operation similarly issues a PUT($a_i{}^{del}, [k]$), but maintains a deletion marker which is used during merge in compaction to remove the deleted entry. Figure 5 depicts the update of index table by the Lazy update strategy upon the PUT in Example 3.

LOOKUP(A_i, a, K): Since the postings list for a could be scattered in different levels, a query LOOKUP needs to merge them to get

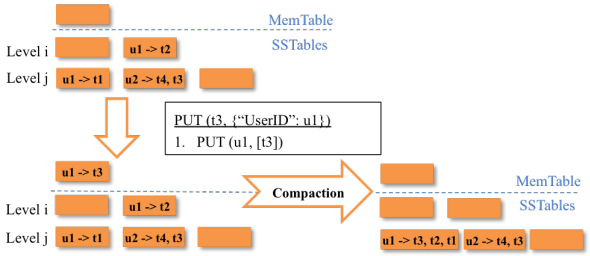


Figure 5: Stand-Alone Lazy Index and its compaction.

a complete list. For this, it checks the MemTable and then the SSTables, and moves down in the storage hierarchy one level at a time. Note that at most one postings list exists per level. Similar to Eager Index, we need to retrieve the data and check validity of a matching record by issuing a GET operation on primary table. Note that, as levels are sorted based on time in the LSM tree, if we already find top-K during a scan in one level, LOOKUP can stop there, and it does not require to go to next level.

RANGELOOKUP(A_i, a, b, K): To support range query in Lazy Index, we modified the primary key range query API in LevelDB. The original range iterator iterates through a range and does not scan a key within the range in lower levels if it already exists in an upper level. We force the iterator to scan level by level (same as LOOKUP). For each level it will look for all the secondary keys for a given range [a,b]. As each key in that range can be fragmented into different levels, a range query needs to traverse each level separately. Similarly to Eager Index, for each secondary key, it adds the associated posting lists' primary keys to a min-heap, which is sorted based on the sequence number (which we include in each entry in the list). Pseudocodes of LOOKUP (Algorithm 3) and RANGELOOKUP (Algorithm 6) on Lazy Index are presented in Appendix B.

4.2 Stand-Alone Index with Composite Keys

PUT(k, $\{A_i : a_i\}$)/DEL(k): Here, the composite key is the concatenation of the secondary and the primary keys, and the value is set to null. Figure 6 depicts the update of index table for Composite Index upon PUT in Example 3. Similarly to Lazy Index, a DEL operation

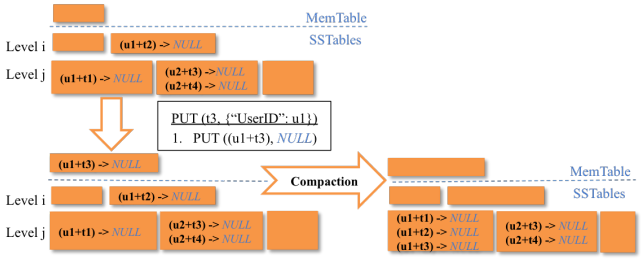


Figure 6: Stand-Alone Composite Index and its compaction.

inserts the composite key with a deletion marker in index table. During compaction, this marked entry is used to detect and remove the deleted entry.

LOOKUP(A_i, a, K): LOOKUP on secondary key performs a prefix range scan on Stand-Alone Index. This scan returns all primary

keys where the secondary key is a prefix of the primary key in the Stand-Alone Index. At each iteration, the iterator breaks the composite key to perform the prefix check. Note that, unlike in Lazy Index, LOOKUP needs to traverse all levels to find top-K entries. In LevelDB, a compaction in a level takes place as round-robin basis, based on SSTable's primary key range in that level. We use composite keys as the primary key of index table. These composite keys associated with a secondary key in a level may span into multiple SSTable files where any one of them can participate in compaction and merges with next level. Hence, given a secondary LOOKUP key, we cannot conclude that these composite keys associated with that secondary key in different levels are sorted based on insertion time in primary table.

RANGELOOKUP(A_i, a, b, K): The RANGELOOKUP operation also uses that prefix based range lookup. Here instead of one prefix, it will traverse for all keys in where it's a prefix of an entry within the range [a,b]. Note that for each match in LOOKUP and RANGELOOKUP, Composite Index also performs a GET operation on the data table similarly to Lazy and Eager Index to retrieve the data record, and then checks its validity. The pseudocodes of LOOKUP (Algorithm 4) and RANGELOOKUP (Algorithm 7) on Composite Index are presented in Appendix B.

4.3 Cost Analysis

Cost of GET/PUT/DEL queries. Stand-Alone Indexes do not incur any overhead on GET queries. However, for a PUT/DEL query on the data table, a Read-Update-Write process is issued on the index table by the Eager Index variant, in contrast to only one write on the index table in the Lazy and Composite Index variant. PUT/DEL overhead is linear to the number of secondary indexes in Stand-Alone Indexes. However, as Stand-Alone Indexes maintain separate tables compared to Embedded Index, they incur additional compaction cost for each index table which heavily affects write performance. Compaction cost depends on write amplification factor $WAMF$ (i.e. the number of times the same record is written to the disk). Lazy and Composite compaction suffer same write amplification as a leveldb primary table, because they write a simple key value pair on every write to the index table. The cost of WAMF has been shown to be $2 \cdot (N+1)(L-1)$, where N is the ratio of the sizes of two consecutive levels [9, 21]. N is set as 10. Compared to Composite, Lazy Index has some extra CPU overheads (e.g. parsing and merging each json posting list during compaction, handling large lists which do not fit inside a block etc.) during compaction. Eager Index suffers huge write amplification on index table as it updates the posting list for every write. Let us assume, average size of the posting list in Eager Index is PL_S. That means a record in the list has already been re-written PL_S times by the eager update strategy. Now $WAMF$ for Eager Index becomes $PL_S \cdot 22 \cdot (L-1)$, where $22 = 2 \cdot (10+1)$. Note that $WAMF$ for primary table is the same for all indexing techniques and therefore omitted from the analysis.

Cost of LOOKUP and RANGELOOKUP queries. For Eager Index, only one read on the index table is needed to retrieve the postings list[1], as all lower level lists are invalid. In contrast, in Lazy Index, a read on the index table may involves up to L (number of levels) disk accesses (because in the worst case the postings list is scattered across all levels). Then, for each matched key in the top-K list, it issues a GET query on the data table to retrieve the actual record. Hence, if there exists K' matched entries for LOOKUP(A_i, a, K), it takes a total of $K'+1$ and $K'+L$ disk accesses for Eager and Lazy Index respectively. Note that we find our top-K entries from K' matched entries (i.e. $K' \geq K$). For the Composite Index, a read on the index table may involve up to L block accesses. Here we assume that result secondary keys fit in one block for Lazy/Composite Index. However, as discussed in Section 4.1.2 and 4.2, Lazy can stop after scanning just one level, if the top-K results are found, whereas Composite Index needs to traverse down to the lowest level to compute the top-K results. This is why Lazy Index performs better for smaller top-K LOOKUP queries than Composite Index. When there is no limit on top-K, both Lazy and Composite have same I/O cost of L, but Lazy has non-negligible CPU cost for maintaining posting lists as discussed earlier. For RANGELOOKUP query, if there exist M blocks in index table that contain a secondary key within the range, in the worst case all the variants need to access all M blocks. Here again for K' matched entries, Stand-Alone Indexes issue K' GET queries on data table. Table 5 shows the worst-case number of disk accesses for different operations in Stand-Alone Indexes.

Table 5: Disk accesses for operations in Stand-Alone Indexes. Assume l attributes are indexed on the primary table. (means that CPU cost cannot be neglected, * means that average case is much better)**

Operation	Index Type	Data Table I/O		Index Table I/O		
		Read	Write	Read	Write	WAMF
GET	All	1	0	0	0	0
PUT, DEL	Eager	0	1	l	l	$l \cdot PL_S \cdot 22 \cdot (L-1)$
	Lazy	0	1	0	l	$l \cdot 22 \cdot (L-1)$ **
	Composite	0	1	0	l	$l \cdot 22 \cdot (L-1)$
LOOKUP	Eager	K'	0	1	0	0
	Lazy	K'	0	L*	0	0
	Composite	K'	0	L	0	0
RANGE LOOKUP	All	K'	0	M	0	0

We summarize the notations used in the algorithms and cost analysis in Table 6.

Table 6: Notation

top-K or K	Most recent K entries based on database insertion time.
(k, v)	key(k)-value(v) pair.
L	Number of levels in the store.
PL_S	Average length of secondary index posting lists.
K'	Number of matched entries for LOOKUP/RANGELOOKUP.
l	Number of secondary indexed attributes.
M	Number of blocks in Index Table with secondary key within given range of RANGELOOKUP query.
fp	Bloom filter false positive rate.

5 EXPERIMENTS

All experiments are conducted on a machine powered by an eight-core Intel(R) Xeon(R) CPU E3-1230 V2 @ 3.30GHz CPUs, 16GB memory, 3TB WDC (model WD3000F9YZ-0) hard drive, with CentOS release 6.9. All the algorithms are implemented in C++ and compiled by g++ 4.8. In our experiments, we set the size of the bloom filter to 100 (See Appendix A.3), which we found to be a

[1] assuming there is no false positive by bloom filters on primary key in the index table

suitable number for our datasets, as discussed in Appendix C.1. We use the default compression strategy of LevelDB, Snappy [22], which compresses each block of an SSTable (see Appendix C.2 for experiments with uncompressed blocks). No block cache was used and the $max.open.files$ is set to large number (30000) so that most of the bloom filters and other metadata can reside in memory.

5.1 Workload

There are several public workloads for key-value store databases available online such as YCSB [6]. However, as far as we know there is no workload generator which allows fine-grained control of the ratio of queries on primary to secondary attributes. Thus, to evaluate our secondary indexing performance, we created a realistic Twitter-based operations (GET, PUT, LOOKUP, RANGELOOKUP) workload generator [30], which is a able to generate two types of workloads: *Static* and *Mixed*. The Static one first does all the insertions, builds the indexes and then performs queries on the static data. Static workloads can isolate GET, PUT, LOOKUP and RANGELOOKUP performance. In contrast, Mixed has continuous data arrivals, interleaved with queries on primary and secondary attributes simulating real workloads. Next, we show how to build a large synthetic tweets dataset based on a seed one. Then, we show how we generate Static and Mixed operation workloads, given a dataset of tweets.

Synthetic dataset generator. Our dataset generator inputs a "seed" set of tweets, a set of secondary (to be indexed) attributes (e.g., UserID, time, place), and a scale parameter, and generates a synthetic dataset, which maintains the attribute value distributions in the seed set. In particular, for each generated tweet, we pick a UserID (or any other attribute, except time which has a special treatment as we discuss below) based on the distribution of UserID's in the seed set, that is, users with more tweets in the seed set will be assigned to more synthetic tweets. Figure 7 shows the rank-frequency distribution of UserID attribute (i.e. number of tweets posted by a user) in our seed dataset. The number of tweets per second is selected based on a uniform distribution with minimum set to 0 and maximum equal to two times the average number of tweets per second in the seed set. We also generate a body (text) attribute with length picked randomly from the seed set, and random characters. The reason we create a body attribute, although it is not used as a secondary key, is to make the experiments more realistic, in terms of number of records that can fit in a primary table block.

Seed dataset. We collected 18 million tweets with overall size 10 GB (in JSON format) through Twitter Streaming API, which have been posted and geotagged within New York State. This took about 3 weeks, which motivates why we build a synthetic tweet generator. The average number of tweets per user is 30 and the average number of tweets per second is 35. The average size of a tweet is 550 Bytes, each containing 22 attributes.

Operations workload generator. The *Static workload generator* inputs (a) a set of tweets, (b) a number n of GETs (or LOOKUPs or RANGELOOKUPs), and (c) the selectivity (for RANGELOOKUPs only), and generates n query operations of the desired type. All input tweets are first inserted (PUT) and then the query operations are executed. The *Mixed workload generator* inputs (a) a set of tweets, (b) a total number n of operations (PUTs, GETs, or LOOKUPs), (c) the frequency ratios between these three operations, and (d) the ratio of PUTs that insert an existing primary key (TweetID). We refer to the latter as "Updates" below. In both generators, the conditions of the query operations are selected based on the distribution of values in the input tweets dataset.

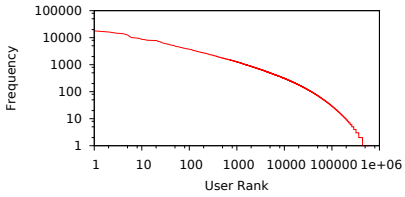


Figure 7: Distribution of UserID attribute in Seed Dataset.

Workloads used in experiments. In our experiments, we set the scale parameter in the dataset generator to 10 and generate a 100GB dataset with 180 million tweets using the workload generator. Using larger datasets would be challenging, given that the experiments took more than one month to run for the 100GB dataset, mainly due to the slow execution of the Eager Index. In the operations workload generator we selected UserID and CreationTime as two secondary attributes; CreationTime is time-correlated (expected to have a good performance for Zone Maps), but UserID is not. Table 7 summarizes different parameters and their values used to generate Static and Mixed workloads for our experiments.

Table 7: Parameters and values for different workloads.

(a) Static Workload

Number of Op n				Selectivity		Top-K
PUT	GET	LOOKUP	RANGE LOOKUP	UserID (in no of users)	CreationTime (in minutes)	
180 million	100K	15K (each index)	50K (each index)	10, 100	1, 100	10, 100, No Limit

(b) Mixed Workloads

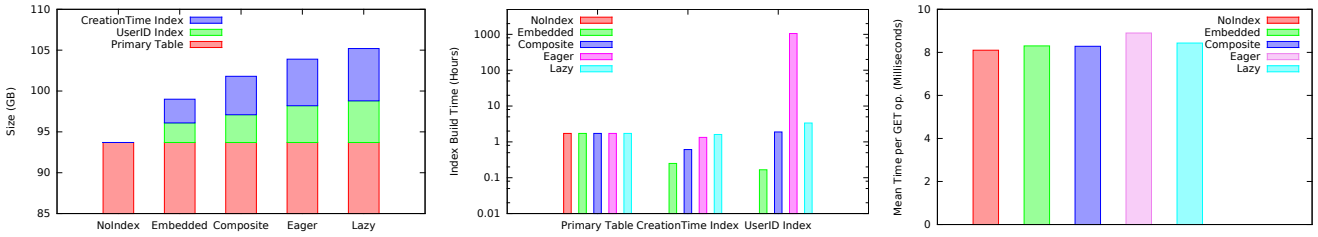
Workload Type	Operation Frequency Ratios				n	Top-K
	PUT	GET	LOOKUP	Update		
Write heavy	80%	15%	5%	0%	50 million	10
Read heavy	20%	70%	10%	0%		
Update heavy	40%	15%	5%	40%		

5.2 Experimental Evaluation

In this section we evaluate our secondary indexing techniques on LevelDB++.

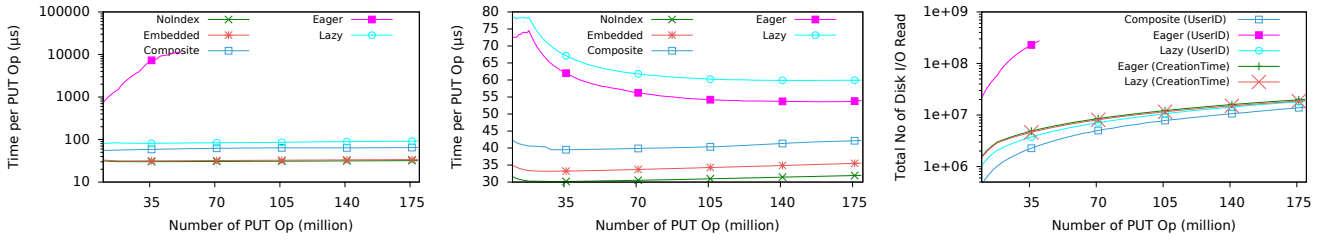
5.2.1 Results on Static workload.

Overhead on Basic LevelDB Operations. Figure 8 shows how the performance of basic leveldb operations is affected by the various secondary index implementations, in terms of size and mean operation execution time for our Static workload. Figure 8a shows that as Embedded Index does not maintain separate index table, it is more space efficient than Stand-Alone Indexes and close to having no index. Eager and Lazy Indexes have JSON overhead to maintain the posting lists, which makes them less space efficient than Composite Index. Lazy has fragmented posting list throughout different levels, whereas Eager Index has more compact list, hence Eager consumes less space than Lazy. Figure 8c shows that all the index variants have identical GET performance with negligible difference.



(a) Database size (b) PUT Performance (c) GET Performance

Figure 8: Performance of different index variants for basic leveldb operations.



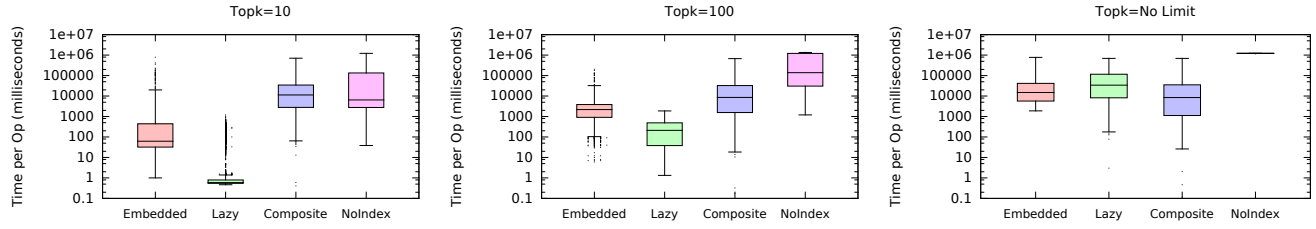
(a) Mean PUT latency (UserID) (b) Mean PUT latency (CreationTime) (c) Cumulative I/O cost for index compaction

Figure 9: PUT performance for different index variants over time.

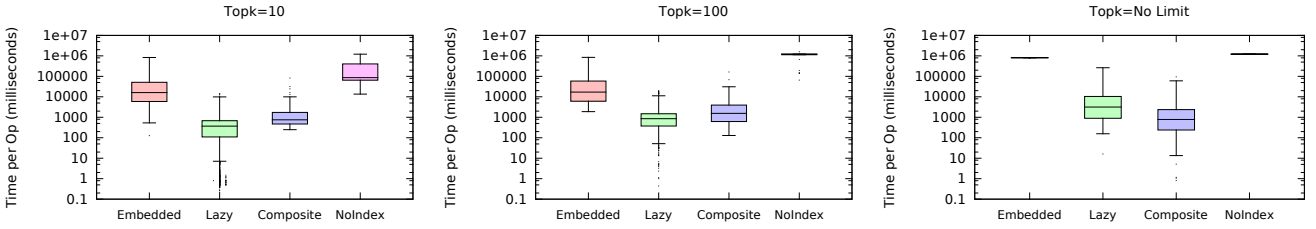
Figure 8b shows the PUT performance for different index variants. We isolate the creation time of primary index and two secondary indexes (CreationTime and UserID). That is, the CreationTime Index time shows the difference between the time of PUT when we only have one secondary index (on CreationTime) minus the PUT time when there is no secondary index. If we add the three times, we get the total PUT time for each index. We see that for both secondary indexes, Embedded Index outperforms the Stand-Alone indexes. Composite shows best PUT performance among Stand-Alone Indexes. Eager performs extremely bad for UserID index because of high write amplification and expensive merge compactions. Figure 9 shows how PUT performance varies over time as the database grows. We took reading after each million insertions. PUT performance remains almost identical for both the attribute index as the database grows (Shown in Figure 9a and 9b) except the Eager Index. Figure 9c shows that merge compaction for Eager Index is exponentially costly for UserID index as the database grows. Eager Index shows good performance for the time-correlated CreationTime index, because the posting list is created sequentially and there is no random list update, hence there are fewer compactions.

Relationship to theoretical analysis. Figures 8b and 9 support the analysis in Sections 3.1 and 4.3, which show that Embedded Index incurs negligible overhead on writes (I/O cost is 1), whereas the Stand Alone Indexes need to perform additional disk accesses. Specifically, for Eager Index it is 1+l+l = 5 (l=2), for Lazy and Composite it is 1+l=3. In addition, each Stand-Alone Indexes suffers high Write Amplification ($WAMF$) contributing to extra compaction cost. $PL_S = 30$ for UserID and $PL_S = 35$ for CreationTime index. We compute the $WAMF$ for each indexing techniques $WAMF_{Eager} = 30 \cdot 22(4-1) + 35 \cdot 22(4-1) = 4290$ ($L = 4$ in the index tables). $WAMF_{Composite} = WAMF_{Lazy} = 2 \cdot 22(4-1) = 132$. These numbers are supported by Figure 9c. Section 4.3 explains and Figure 8b confirms that Lazy has higher CPU cost (** in Table 5) than Composite Index. Table 3 and 5 also supports Figure 8c, which shows that there is no overhead on GET (reads on primary index). The negligible difference (less than 1 *milliseconds*) between the GET of different approaches may be attributed to OS buffer cache or background compactions, due to the additional storage space required by the secondary indexes.

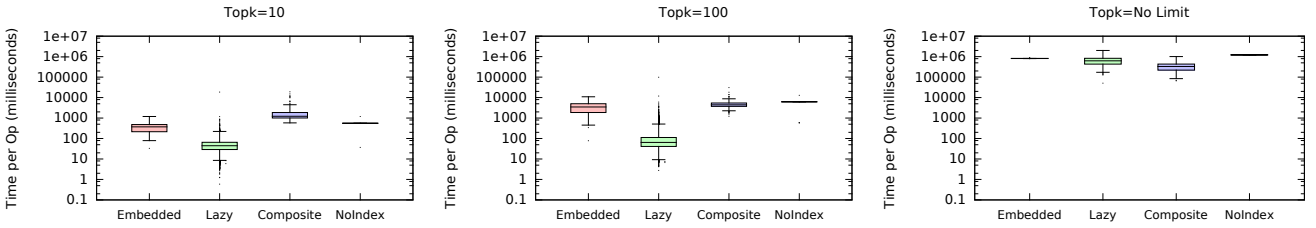
Query (LOOKUP, RANGELOOKUP) Response Time: Figure 10 shows the latency of LOOKUP (10a) and RANGELOOKUP (10b, 10c) with different selectivity and top-K of different index variants on non time-correlated index attribute UserID. Eager Index is excluded from these experiments because we already found out it is unusable for high write amplification and costly merge compaction. Here, latency for different queries are presented in box-and-whisker plots where quartile boundaries are determined such that 1/4 of the points have a value equal or less than the first quartile boundary, 1/2 of the points have a value equal or less than the second quartile (median) value, etc. A box is drawn around the region between the first and third quartiles, with a horizontal line at the median value. Whiskers extend from the ends of the box to the most distant point whose y value lies within 1.5 times the interquartile range. These figures show that Lazy Index performs best when top-K is small for LOOKUP queries. Composite Index performs best when top-K is bigger or there is no restriction of top-K (i.e. return all results). But when K is small Embedded Index also outperforms Composite Index. Stand-Alone Indexes outperform Embedded Index for RANGELOOKUP queries, as zone maps are not useful for non time-correlated attribute. Similar to LOOKUPs, Lazy performs best for RANGELOOKUP queries when top-K is smaller, otherwise Composite outperforms Lazy. Embedded Index performs better for higher selectivity and outperforms Composite Index if top-K is smaller as



(a) LOOKUP Response Time



(b) RANGELOOKUP Response Time (Selectivity: 10)



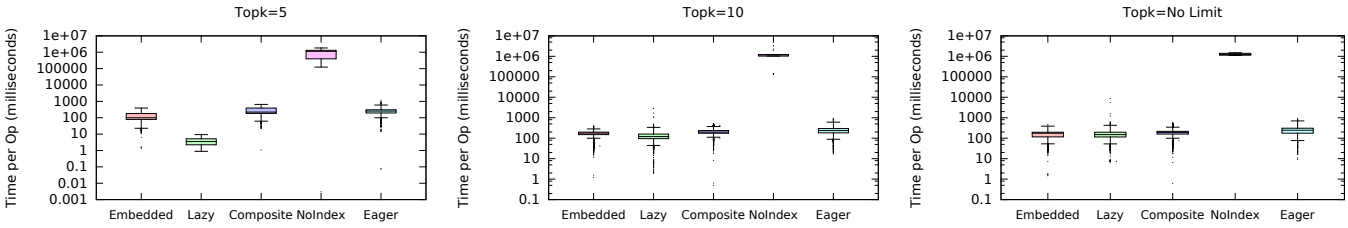
(c) RANGELOOKUP Response Time (Selectivity: 1000)

Figure 10: UserID Index performance for different variants varying Selectivity and TopK.

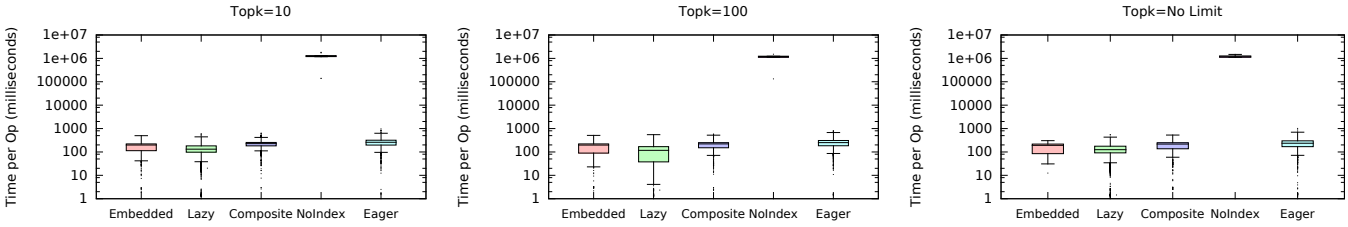
Embedded can find top-K results in top levels for higher selectivity queries. Figure 11 shows query response performance for time-correlated CreationTime index attribute. Similar to UserID index, Lazy outperforms all index for LOOKUP queries (Figure 11a). For RANGELOOKUP queries, Embedded Index outperforms Stand-Alone Indexes for all selectivity factors because its zone maps are very most effective on time-correlated index attributes (Figure 11b, 11c). As the selectivity increases, Composite outperforms Lazy and Eager Index.

Relationship to theoretical analysis. The cost analysis in Tables 3 and 5 supports our experimental results in Figures 10a and 11a. These figures show that Lazy Index is sensitive to top-K for LOOKUP queries and performs better than Composite Index for smaller top-K queries on average, whereas Composite Index outperforms Lazy when there is no limit on top-K. Our experimental results show that the CPU cost (** in Table 3) dominates the Embedded Index LOOKUP performance and it performs worse than Stand-Alone Indexes for non-time-correlated UserID Index. However, for time-correlated index attribute CreationTime, Figure 11a supports our analysis that zone maps have strong pruning power for time-correlated indexes and Embedded Index performance is comparable to Stand-Alone Indexes. For RANGELOOKUP queries, the cost analysis in Table 3 supports the experimental results in Figures 10b and 10c, which show that Embedded Index (i.e. Zone Maps) does not perform well for non time-correlated Index and almost perform same as no index. However, Figures 11b and 11c show that zone maps are powerful for RANGELOOKUP queries on time-correlated index and their better pruning power makes the disk access cost close to K.

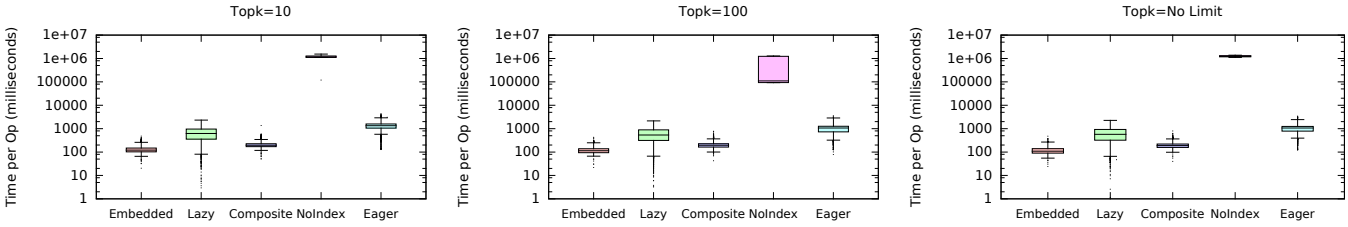
5.2.2 Results on Mixed workloads. Figures 12a, 12b and 12c show the overall performance of index variants in terms of mean time per operation for different Mixed workloads (write, read and update heavy respectively). Only the UserID attribute is indexed and queried. We record the performance once per 1 million operations. We did not consider Eager Index as it is shown to be unusable in previous discussions. It is difficult to isolate the performance of individual operations as one operation might incur overhead on the system and ultimately interfere with another operation. Also, the mean time per operation is not a good metric for performance measurement as we have seen in Figure 10. To properly measure the performance of individual operations, we record the cumulative number of disk I/O as the database grows along with the mean time per operation. Figures 13, 14, and 15 represent the individual GET, PUT and LOOKUP performance of index variants in terms cumulative number of disk I/O for write, read and update heavy workloads respectively. We see that for different Mixed workloads, Lazy always perform better than the other indexes in terms of overall mean operation latency. Embedded Index does not perform well for read heavy workloads, as expected for non-time correlated index attribute UserID (Figure 12b). There is an unusual jump for



(a) LOOKUP Response Time

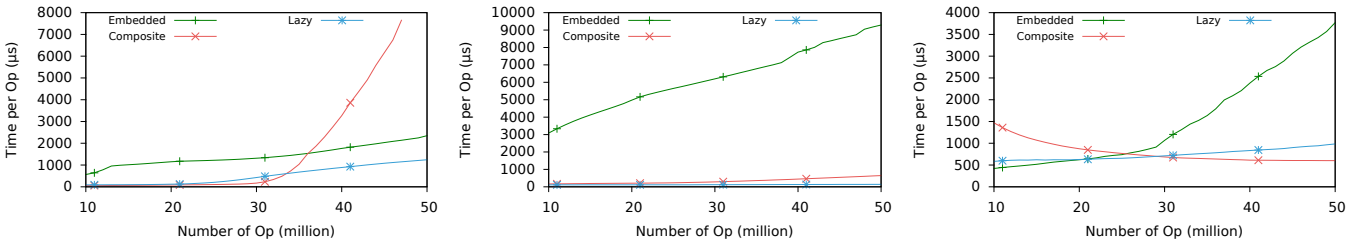


(b) RANGELOOKUP Response Time (Selectivity: 1 min)



(c) RANGELOOKUP Response Time (Selectivity: 100 min)

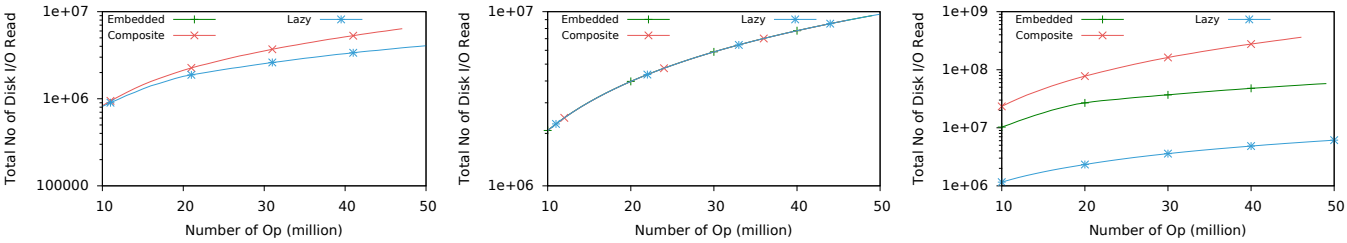
Figure 11: CreationTime Index Performance for different variants varying TopK and selectivity.



(a) Write Heavy Workload (b) Read Heavy Workload (c) Update Heavy Workload

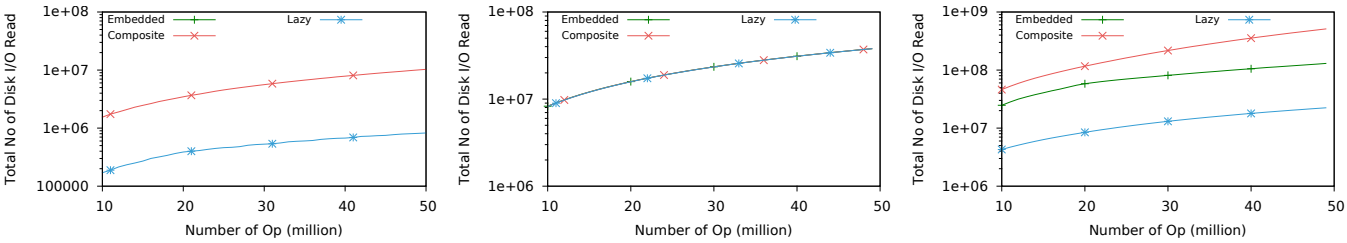
Figure 12: Overall performance comparison for Write, Read and Update Heavy workloads

Composite Index performance in write heavy workload (Figure 12a). The inflection point occurs at 30-35 million operations, which equals about 16GB of data which is the RAM size. At that point, the GET starts being very expensive as OS buffer cache becomes more ineffective. Beyond that point, the relationship between the performance of the various indexes stabilizes, which implies that our observations would likely also hold for bigger datasets. A Composite Index LOOKUP needs to perform many GET operations even for small top-K; these GETs dominate the overall performance. Composite Index shows slightly better performance than Lazy in the update-heavy workload (Figure 12c) as the database grows. The updates incur frequent compaction in Index Table, and compaction is heavier in Lazy than Composite Index because of the Json parsing overhead for maintaining lists. We also see that the Embedded Index starts to perform bad once the number of updates grows, as these updates result in extra rounds of compaction. We compare the compaction I/O costs for different workloads in Figures 13a, 14a and 15a. Embedded Index has higher cost only when there are updates on the primary table. Figures 13b, 14b and 15b show the same cost for GET operations as expected for all index variants. For LOOKUP (Figures 13c, 14c and 15c), Lazy always outperforms Composite and Embedded as the index is non-time-correlated and top-K is smaller. LOOKUPs in Embedded Index perform worse in the update-heavy workload.



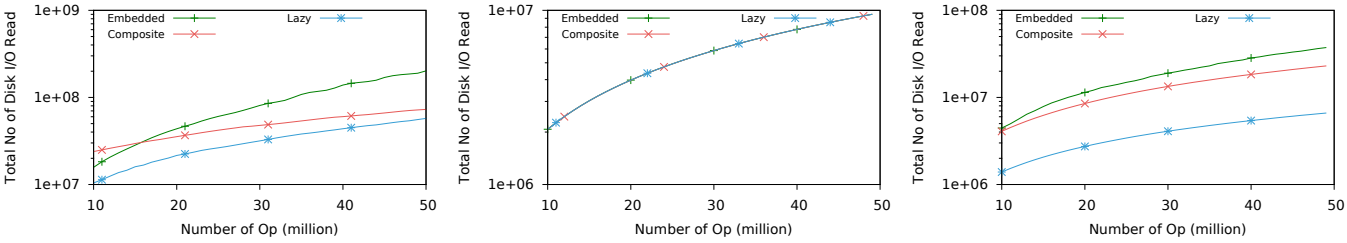
(a) Cumulative Disk I/O cost in Compaction (b) Cumulative Disk I/O cost for GET (c) Cumulative Disk I/O cost for LOOKUP

Figure 13: Performance in Write Heavy workload for different index variants



(a) Cumulative Disk I/O cost in Compaction (b) Cumulative Disk I/O cost for GET (c) Cumulative Disk I/O cost for LOOKUP

Figure 14: Performance in Read Heavy workload for different index variants



(a) Cumulative Disk I/O cost in Compaction (b) Cumulative Disk I/O cost for GET (c) Cumulative Disk I/O cost for LOOKUP

Figure 15: Performance in Update Heavy workload for different index variants

The reason behind unusual jumps in performance for both Embedded and Stand-Alone Indexes in Mixed workloads (Figure 12b) is because of an increase in OS block cache miss after a while. LSM-tree relies on frequent compaction operations to merge data into a sorted structure. After a compaction, the original data are reorganized and written to other locations on the disk. As a result, the cached data are invalidated, since their referencing addresses are changed, causing serious performance degradations. Because LOOKUP and RANGELOOKUP read lots of random disk blocks resulting bad cache performance eventually for any system. Various optimizations to overcome this problem are being studied and can be applied to our LevelDB++ [14] [32].

5.2.3 Summary of novel results. We next summarize the results that have not been reported or adequately documented in previous work. First, Eager Index shows poor performance during ingestion and does not scale well with large datasets, even though it is currently widely used in several systems for its ease of implementation and fast query response time. Second, the combination of Embedded Indexes (i.e. zone maps and bloom filters) provides a lightweight indexing option, which is effective even for non time-correlated index attributes. However, no existing system, to our knowledge, employs them for secondary indexes. Third, Composite Index performs worse than Lazy for top-K LOOKUP queries, which are common in many modern applications (e.g. social networks, messaging apps etc.). However, due to the ease of implementation, Composite indexes are more widely used in such applications. Finally, the effect of buffer cache cannot be neglected during a real system workload, as shown in Figure 12.

6 CONCLUSIONS

We studied five secondary indexing methods for LSM-based NoSQL stores, namely Eager, Lazy and Composite (Stand-Alone Indexes), and Zone maps and Bloom filters (Embedded Indexes). We built a system, LevelDB++, which implements these indexing methods on top of LevelDB, and conducted extensive experiments to examine their performance. The experimental results show the trade-offs between these indexing techniques. We present guidelines to pick the right indexing techniques for different workloads and applications.

ACKNOWLEDGMENTS

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Appendices

The appendix is organized as follows. Appendix A reviews background on LSM-tree, LevelDB storage architecture and Bloom Filter. Appendix B provides pseudocode of LOOKUP (A_i, a, K) and RANGELOOKUP (A_i, a, b, K) operation in LevelDB implementation for different index variants. Appendix C presents supplementary experimental results, which analyze the effect of bloom filter, compression and concurrency on different secondary indexes. Appendix D describes effect of distributed environment on secondary indexes.

A BACKGROUND

A.1 LSM tree

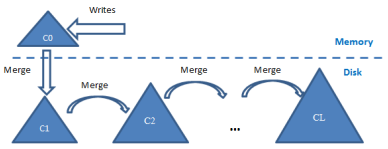


Figure 16: LSM tree components.

An LSM tree generally consists of an in-memory component (level in LevelDB terminology) and several immutable on-disk components (levels). Each component consists of several data files and each data file consists of several data blocks. As depicted in Figure 16, all writes go to in-memory component (C0) first and then flush into the first disk component once the in-memory data is over the size limit of C0, and so on. The on-disk components normally increase in size as shown in Figure 16 from C1 to CL. A background process (compaction) will periodically merge the smaller components to larger components as the data grows. Delete on LSM is achieved by writing a tombstone of the deleted entry to C0, which will later propagate to the component that stores this entry. LSM is highly optimized for writes as a write only needs to update the in-memory component C0. The append-only style updates mean that an LSM tree could contain different versions of the same entry (different key-value pairs with the same key) in different components. A read (GET) on an LSM tree starts from C0 and then goes to C1, C2 and so on until the desired entry is found, which makes sure the newest (valid) version of an entry will be returned. The older

versions of an entry (either updated or deleted) are obsolete and will be discarded during the merge (compaction) process. Conventionally, the in-memory component (C0) is referred as MemTable and the on-disk components are referred as SSTable.

A.2 SSTable in LevelDB

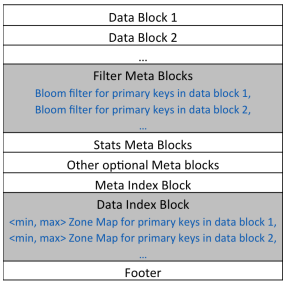


Figure 17: LevelDB SSTable structure.

Here we present some storage details of LevelDB [23] as background for ease of understanding of the paper. Level-$(i+1)$ is 10 times larger than level-i in LevelDB. Each level (component) consists of a set of disk files (SSTables), each having a size around 2 MBs. The SSTables in the same level may not contain the same key (except level-0[2]). Further, LevelDB partitions its SSTables into data blocks (normally tens of KB in size). The format of an SSTable file in LevelDB is shown in Figure 17. The key-value pairs are stored in the *data blocks* sorted by their key. Filter Meta blocks store a bloom filter for each block, computed based on the keys of the entries in that block, to speedup GET operations. Then, there are data index blocks, which we call zone maps for primary table.

A.3 Bloom Filter

Bloom filter [4] is a hashing technique to efficiently test if an item is included in a set of items. Each item in the set is mapped to several bit positions, which are set to 1, by a set of n hash functions. Then, the bloom filter of a set is the OR-ing of all these bitstrings. To check the membership of an item in the set, we compute n bit positions using the same n hash functions and check if all corresponding bits of the bloom filter are set to 1. If no, we return false, else we have to check if this item exists due to possible false positives. The false positive rate depends on the number of hash functions n, the number of items in the set S and the length of the bit arrays m, which can be approximately computed as Equation 1. Given S and m, the minimal false positive rate is $2^{-\frac{m}{S}ln2}$ by setting the $n = \frac{m}{S}ln2$.

$$\left(1 - \left[1 - \frac{1}{m}\right]^{nS}\right)^n \approx \left(1 - e^{-nS/m}\right)^n \quad (1)$$

B ALGORITHMS

In all algorithms, we assume each $tuple(k, v)$ is associated with a sequence number (seq). We show how we add the records on Min-Heap H based on this seq in Algorithm 1. Algorithm 2, 3, 4, 5 present the pseudocodes of LOOKUP(A_i, a, K) in Stand-Alone Eager, Lazy, and Composite Index and Embedded Index respectively.

[2]which is C1 in Figure 16 as LevelDB does not number the memory component

Algorithm 6, 7,8 present the pseudocodes of RANGELOOKUP(A_i, a, b, K) in Stand-Alone Lazy, and Composite and Embedded Index respectively. Stand-Alone Eager Index uses existing range query API for primary key on the Stand-Alone Index Table in LevelDB.

Algorithm 1 Min-Heap $H.Add(K, \langle k, v\rangle)$ Procedure

```
1: if H.size() == K ∧ H.top.seq < ⟨k, v⟩.seq then
2:     H.pop();
3:     H.put(⟨k, v⟩);
4: else if H.size() < K then
5:     H.put(⟨k, v⟩);
6: return
```

Algorithm 2 LOOKUP Procedure using Eager Index

```
1: Create Min-Heap H;
2: Primary key list L ← return of GET(a) on index table T_i. {Suppose the order is maintained as recent key to older keys}
3: for k in L do
4:     ⟨k, v⟩ ← return of GET(k) on data table.
5:     if v.val(A_i) == a then
6:         H.add(K, ⟨k, v⟩) {Algorithm 1}
7:     if H.size() == K then
8:         BREAK
9: return List of pairs in H
```

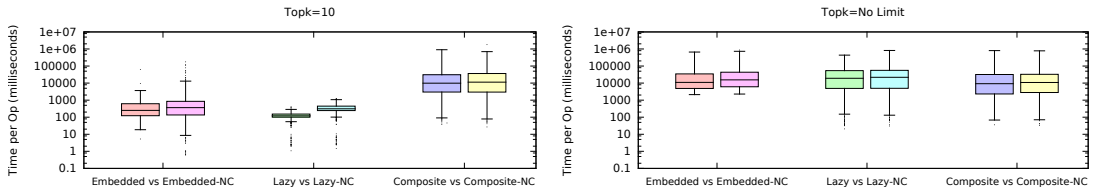
Algorithm 3 LOOKUP Procedure using Lazy Index

```
1: Create Min-Heap H;
   {starts from MemTable (C0) and then moves to SSTable, C1 is LevelDB's level-0 SSTable.}
2: for j from 0 to L do
3:     if val(A_i) is not in Cj then
4:         NEXT
5:     List of primary keys P ← val(A_i) in Cj
6:     for k in P do
7:         ⟨k, v⟩ ← return of GET(k) on data table.
8:         if v.val(A_i) == a then
9:             H.add(K, ⟨k, v⟩) {Algorithm 1}
10:        if H.size() == K then
11:            return H
12: return List of pairs in H
```

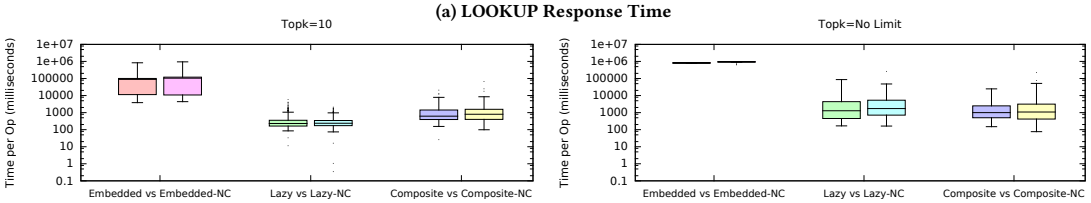
C SUPPLEMENTARY EXPERIMENTS

C.1 Effects of varying bloom filter lengths

The length of each bloom filter used in Embedded Index also has effect on LOOKUP performance in two folds: (1) with larger bloom filter, the false positive rate will drop thus the number of blocks to be loaded into memory is smaller, and (2) the cost of checking each bloom filter is higher because more hash functions are applied for each key to check its existence as the bloom filter length increases. We conducted the experiment by varying the value of *bits per key* from 20 to 1000 with our seed twitter dataset to determine the optimal choice of bloom filter length for this dataset. We write 20



(a) LOOKUP Response Time



(b) RANGELOOKUP Response Time (Selectivity: 10)

Figure 18: UserID Index performance for different variants with and without compression. (NC = Not Compressed)

Algorithm 4 LOOKUP Procedure using Composite Index

```
Create Min-Heap H;
{starts from MemTable (C0) and then moves to SSTable, C1 is LevelDB's level-0 SSTable.}
for j from 0 to L do
    it ← SSTable :: Iterator_j.SEEK(a)
    while it.valid() do
        Composite key, ckey ← it.key()
        skey ← ckey.ExtractSecondarykey()
        if a == skey then
            k ← ckey.ExtractPrimaryKey()
            ⟨k, v⟩ ← return of GET(k) on data table.
            if v.val(A_i) == a then
                H.add(K, ⟨k, v⟩) {Algorithm 1}
        else if skey > a then
            BREAK
        it.NEXT()
return List of pairs in H
```

Table 8: How LOOKUP performance, average false positive rates and database size vary with bloom filter length

Bits Per Key	DB Size (MB)	False Positive %	Mean LOOKUP Latency (Milliseconds)
20	10,127	0.64%	52
50	10,256	0.44%	49
100	10,470	0.08%	21
200	10,899	0.08%	20.5
500	12,186	0.08%	22
1000	14,325	0.08%	32

million tweets with Embedded Index on UserID and performed 200K LOOKUPs. Table 8 shows the average performance of LOOKUPs. Here we see that the LOOKUP performance starts to increase with increasing bits per key setting of bloom filter (20 to 200) as the false positive rate decreases. But then the performance decreases with larger value of bits per key where the false positive rate is low enough, but the cost of checking bloom filters increases. We also show the space trade-offs in Table 8. As the bits per key increases, the bloom filter takes more space. In our experiments, we set *bits per key* as 100, because the LOOKUP performance is very close to setting it as 200 to 300 but with reasonable space overhead.

C.2 Effect of compression on indexes

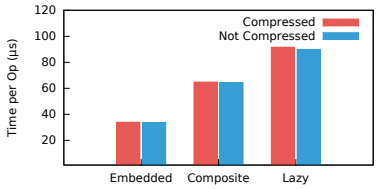


Figure 19: Mean Time per PUT operation on UserID index

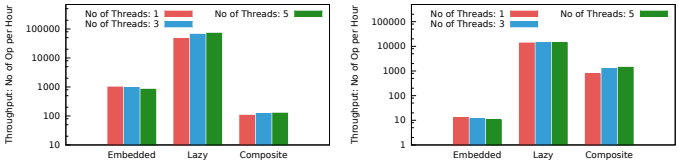
In this section, we report how block compression affects secondary index's performance. Keeping same experimental settings and same dataset from Section 5, we rebuild our secondary indexes for UserID index without compression and perform top-K LOOKUP and RANGE LOOKUP queries. Figures 18a and 18b show varying top-K LOOKUP and RANGELOOKUP query response times of different secondary indexes, for default Snappy compression [22] enabled against no compression. We see the same relationship exists between different indexing variants with or without compression. But LOOKUP and RANGELOOKUP response times are slightly higher for all of them if there is no compression enabled. Figure 19 shows that we also get almost identical results for PUT performance for all secondary indexes with and without compression.

C.3 Effect of multi-threaded environment

In this section, we report our secondary index's performance in multi-threaded environment. We repeat LOOKUP and RANGE LOOKUP queries from Section 5 on UserID index and measure throughput (i.e. number of operation per hour) varying number of concurrent threads. Top-K is set as 10. Figure 20 shows that secondary indexes show same relationship between them for multi-threaded environment compare to single thread. Stand-Alone Indexes has slightly higher throughput for high concurrencies over Embedded Index because different threads can efficiently access data and index table in parallel. Although, we see that increasing

Algorithm 5 LOOKUP Procedure using Embedded Index

1: **function** *GetLite* $(key, level)$
2: **for** $l = 0 \rightarrow L$ **do**
3: **if** $l.SEEK(key) == True$ **then**
4: **if** $l = level$ **then**
5: **return** True {SEEK operation Checks only in-memory metadata, index block and bloom filters for primary key to lookup key}
6: **else**
7: **return** False
1: **function** *LOOKUP* (A_i, a, K)
2: Create Min-Heap H;
3: **for** table in MemTable **do**
4: **for** $\langle k, v \rangle$ in table **do**
5: **if** $val\,(A_i) == a$ **then**
6: H.add(K, $\langle k, v \rangle$) {Algorithm 1}
7: **if** $H.size\,() == K$ **then**
8: **return** List of K pairs in H
9: **for** $l = 0 \rightarrow L$ **do**
10: **for** $sstable_j$ in level-l **do**
11: **if** $sstable_j.globalzonemap\,(A_i)\,.contains\,(a) == True$ **then**
12: **for** block b_m in $sstable_j$ **do**
13: **if** $b_m.bloomfilter\,(A_i)\,.contains\,(a) == False$ **or** $b_m.zonemap\,(A_i)\,.contains\,(a) == False$ **then**
14: NEXT
15: load b_m of $sstable_j$ in memory;
16: **for** $\langle k, v \rangle$ in b_m **do**
17: **if** $v.val\,(A_i)\,.equals(a) \wedge GetLite(k, l) == True$ **then**
18: H.add(K, $\langle k, v \rangle$) {Algorithm 1}
19: **if** $H.size\,() == K$ **then**
20: **return** List of K pairs in H
21: **return** List of pairs in H



(a) LOOKUP Throughput **(b) RANGELOOKUP Throughput**

Figure 20: UserID Index performance for multi-threads

the number of threads does not necessarily increase throughout much (even decrease throughput in some cases) as different threads compete with each other for system resources (e.g. database components) and eventually decrease system throughput.

D EFFECT OF DISTRIBUTED ENVIRONMENT

The main overhead of a distributed NoSQL environment is the cost of maintaining the replication consistency [29]. In this paper, we focus on the storage engine module, which can be conceptually

Algorithm 6 RANGELOOKUP Procedure using Lazy Index

1: Create Min-Heap H;
{starts from MemTable (C0) and then moves to SSTable, C1 is LevelDB's level-0 SSTable.}
2: **for** j from 0 to L **do**
3: $it \leftarrow SSTable :: Iterator_j.SEEK$(a)
4: **while** $it.valid()$ **do**
5: **if** $it.key()$ in $[a, b]$ **then**
6: List of primary keys $P \leftarrow it.value()$
7: **for** k in P **do**
8: $\langle k, v \rangle \leftarrow$ return of GET(k) on data table.
9: **if** $v.val\,(A_i) == it.key()$ **then**
10: H.add(K, $\langle k, v \rangle$) {Algorithm 1}
11: **else**
12: BREAK
13: $it.NEXT()$
14: **return** List of pairs in H

Algorithm 7 RANGELOOKUP Procedure using Composite Index

1: Create Min-Heap H;
{starts from MemTable (C0) and then moves to SSTable, C1 is LevelDB's level-0 SSTable.}
2: **for** j from 0 to L **do**
3: $it \leftarrow SSTable :: Iterator_j.SEEK$(a)
4: **while** $it.valid()$ **do**
5: Composite key, $ckey \leftarrow it.key()$
6: $skey \leftarrow ckey.ExtractSecondarykey()$
7: **if** $skey$ in $[a, b]$ **then**
8: Repeat $\leftarrow$ Line 8-12 from Algorithm 4
9: **else if** $skey > b$ **then**
10: BREAK
11: $it.NEXT()$
12: **return** List of pairs in H

Algorithm 8 RANGELOOKUP Procedure using Embedded Index

1: Create Min-Heap H;
2: **for** table in MemTable **do**
3: **for** $\langle k, v \rangle$ in table **do**
4: **if** $v.val\,(A_i)$ in $[a, b]$ **then**
5: H.add(K, $\langle k, v \rangle$) {Algorithm 1}
6: **if** $H.size\,() == K$ **then**
7: **return** List of K pairs in H
{REPEAT LINE 9 to 20 from Algorithm 5 to populate H, but replace $contains(a)$ function with $intersects(a, b)$ and $equals(a)$ with $within(a, b)$}
8: **return** List of pairs in H

viewed as a state machine maintained by any consensus protocol-based (e.g. Paxos, Raft) replication engine (e.g. PaxosStore [37]). The overhead of the replication engine generally does not depend on the choice of the implementation of the state machine (i.e. implementation of secondary indexes). The other aspects of distributed environment (i.e. partitioning module, cluster membership etc.) can also be designed independent to the storage engine module [31] [2] [3].