OSM-tree: A Sortedness-Aware Index

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\textbf{ABSTRACT}

Indexes facilitate efficient querying when the selection predicate is on an indexed key. As a result, when loading data, if we anticipate future selective (point or range) queries, we typically maintain an index that is gradually populated as new data is ingested. In that respect, \textit{indexing can be perceived as the process of adding structure to an incoming, otherwise unsorted, data collection}. The process of adding structure comes at a cost, as instead of simply appending incoming data, every new entry is inserted into the index. If the data ingestion order matches the indexed attribute order, the ingestion cost is entirely redundant and can be avoided (e.g., via bulk loading in a B\textsuperscript{+}-tree). However, state-of-the-art index designs do not benefit when data is ingested in an order that is \textit{close to} being sorted but \textit{not} fully sorted.

In this paper, we study how indexes can benefit from \textit{partial data sortedness} or \textit{near-sortedness}, and we propose an ensemble of techniques that combine \textit{bulk loading}, \textit{index appends}, \textit{variable node fill/split factor}, and \textit{buffering}, to optimize the ingestion cost of a tree index in presence of partial data sortedness. We further augment the proposed design with necessary metadata structures to ensure competitive read performance. We apply the proposed design paradigm on a state-of-the-art B\textsuperscript{+}-tree, and we propose the Ordered Sort-Merge tree (OSM-tree). OSM-tree outperforms the state of the art by up to 8.8x in ingestion performance in the presence of sortedness, while falling back to a B\textsuperscript{+}-tree’s ingestion performance when data is scrambled. OSM-tree offers competitive query performance, leading to performance benefits between 28\% and 5x for mixed read/write workloads.

\textbf{PVLDB Artifact Availability:}

The artifacts have been made available at https://github.com/BU-DiSC/osmtree and https://github.com/BU-DiSC/sortedness-workload.

\textbf{1 INTRODUCTION}

Database indexing sits at the heart of almost any data system varying from full-blown relational systems \cite{UCB} to NoSQL key-value stores \cite{Redis}. Indexes help accelerate query processing both for analytical and transactional workloads by allowing efficient data accesses of selective (range or point) queries. Essentially, in presence of read queries, database administrators decide to build and maintain indexes to improve query performance at the expense of space and write amplification \cite{write-amp}, and the time needed to update the indexes.

\textbf{Indexing Adds Structure to Facilitate Queries.} We pay the cost of index construction and maintenance because it \textit{adds structure} to the data, which, in turn, allows for efficient queries. As shown in

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{State-of-the-art indexing and data organization techniques pay a higher write cost in order to store data as sorted (or, in general, more organized) and offer efficient reads. Since the goal of indexing is to store the data as sorted, we ideally expect that ingesting \textit{near-sorted} data would be more efficient, which is not the case. We introduce the OSM meta-design that offers better performance as data exhibit higher degree of sortedness.}
\end{figure}

Figure 1, with the thick black line, every index or, in general, any data organization technique, exhibits a fundamental tradeoff between its \textit{read} and \textit{write} cost. To achieve efficient logarithmic search time for point queries, a classical index would insert data in their correct position (in-order insertion) leading to efficient logarithmic search (bottom right part of the figure). On the other extreme, if read queries are infrequent, then, scanning is acceptable and instead of adding new entries to an index, we can simply append them (appends leading to scans in the top left part of the figure). This read vs. write tradeoff holds for any data organization effort, including, classical indexing like B\textsuperscript{+}-tree \cite{B+tree}, write-optimized log-structured merge (LSM) trees \cite{LSM}, or simple online sorting via in-order insert. Since all such data organization efforts are essentially \textit{adding structure to an otherwise unstructured data collection}, one would expect they benefit when such structure exists already. Indeed, if the data entries are already fully sorted, then we can benefit, for example, by bulk loading a B\textsuperscript{+}-tree. However, a question that remains open is \textit{what happens when the data entries arrive with some degree of structure but are not entirely sorted} (e.g., due to implicit clustering \cite{implicit-clustering, implicit-clustering}). Before addressing this question, we first explain the concept of \textit{data sortedness} and showcase real-life examples of workloads with variable degree of data sortedness.

\textbf{Data Sortedness.} Data Sortedness can be defined as the \textit{arrival order} of the indexed key upon ingestion. This arrival order can be fully sorted, nearly sorted, less sorted, or scrambled. Data entries may be \textit{near-sorted} in several real-world cases. Consider the TPC-H \cite{TPC-H} lineitem table that has three date-related attributes. Figure 2(a), which depicts the first 10,000 values of shipdate, commitdate, and receiptdate of the lineitem table, shows that when the data arrives in order based on shipdate, the other two attributes are very close to also being sorted. There are several scenarios that lead to near-sorted data collections. For example, (i) a relation that was
Figure 2: (a) TPC-H implicit clustering between shipdate, commitdate, and receiptdate leads to near-sorted columns when the data is sorted based on one of them. (b) Ideally, index insertion performance should improve when inserting already sorted or near-sorted data.

sorted but a few new arbitrary updates took place, (ii) data that has been created based on a previous operation or query, e.g., a join, (iii) data that is sorted based on another attribute that is naturally correlated (like the TPC-H example above), or (iv) the timestamp attribute of an incoming data stream that has a few data packets arriving out of order due to network congestion [6].

In order to be able to exploit this near-sortedness, we need a way to quantify it. In fact, there have been multiple sortedness metrics proposed [6, 13, 30]. Several of the sortedness metrics focus on quantifying the number of inversions or transpositions needed to achieve full sortedness [2, 15, 18, 21, 30]. However, a more natural way of thinking about the degree of sortedness in the context of indexing is how many elements are in the “wrong” position and, more crucially, by how much. As a result, we use the $(K, L)$ sortedness metric [6] that quantifies sortedness using two parameters: $K$, that captures the number of elements that are out of order and $L$, that captures the maximum displacement in terms of position of the out of order elements. Going back to the TPC-H example in Figure 2(a), when the data is sorted on shipdate, commitdate has $K = 99.2\%$ and $L = 1.6\%$, while receiptdate has higher sortedness with $K = 96.7\%$ and $L = 0.1\%$. For the latter, this means that 96.7% of the entries are not at the position they would be if they were sorted and the maximum displacement is 0.1% of the data size. The $(K, L)$ metric helps quantify the number of entries we need to work on to absorb sortedness when inserting new data.

**Problem: Indexes Do Not Exploit Data Near-Sortedness.**

While indexes can already benefit from inserting a fully sorted data collection via bulk loading [1, 16] (assuming that it is already known that data is sorted), they are not designed to exploit near-sortedness. Further, widespread buffering techniques to optimize index insertion (like in B*-trees [10] and LSM-trees [32]) are not designed to exploit sortedness and will end up sorting the data even when they are (almost) sorted. We argue that when inserting data to an index, the higher the data sortedness, the lower the insertion cost should be, as depicted in Figure 2(b), for the ideal tree data structure.

Note that state-of-the-art indexes, like B*-trees, do not exhibit any performance improvement when inserting near-sorted data. In fact, if data is inserted in order and bulk loading is not employed, a B*-tree would have the worst-possible space amplification, since every node will be exactly 50% full. In contrast, a sortedness-aware index should achieve a better read vs. write tradeoff as data sortedness increases, as depicted by the dashed lines in Figure 1. Following the green line, which constitutes a third axis – the one for sortedness – we envision a new class of data structures that is able to navigate the entire shaded region in Figure 1 and perform “less” indexing for near-sorted data, leading up to the ideal performance of append-like cost of insertion with efficient searching if data is sorted.

**Our Approach: OSM-tree.** To realize this vision, we propose a new paradigm for designing indexes that is capable of exploiting any existing degree of sortedness to improve index insertion performance without hurting read latency. We achieve this using an ensemble of techniques which, when combined appropriately, solve a problem that cannot be solved by any one of them alone. Specifically, we employ buffering, partial bulk loading, query-driven partial sorting, and merging to create an index ingestion mechanism that substantially accelerates the ingestion performance in the presence of data sortedness. This sortedness-aware approach, however, comes at the cost of increased read latency since every query may have to search a buffer. To alleviate this cost, we augment the design with a collection of Zonemaps [31] and Bloom filters (BFs) [9], which help make the read cost comparable to the baseline. By combining the ingestion and the read optimizations on top of a state-of-the-art B*-tree, we propose our new design termed Ordered Sort-Merge tree (OSM-tree). In a nutshell, OSM-tree buffers incoming data to bulk load as much as possible and reverts back to insertion from the root (top-inserts) otherwise. By adaptively sorting buffered data during queries, OSM-tree avoids the burden of sorting large data collections. With respect to reads, it uses interpolation search for the sorted parts of the buffer, and pays the cost of scanning a small amount of data when the Zonemaps and Bloom filters direct a query to unsorted entries in the buffer. Note that the OSM paradigm can make any tree-based data structure (e.g., radix trees, B*-trees, and LSM-trees) amenable to data sortedness. It is not a new index per se, rather, a new framework for creating sortedness-aware counterparts for any tree-based index.

**Contributions.** Our work offers the following contributions.

- We identify sortedness as a resource that can be harnessed to ingest data faster in tree indexes.
- We propose a new index meta-design that employs buffering, partial bulk loading, and merging to enhance ingestion in the presence of any degree of data sortedness.
- We augment this design to propose OSM-tree that encompasses query-driven sorting, merging, Zonemaps, and Bloom filters to maintain competitive performance for point and range queries.
- We apply this design on a state-of-the-art B*-tree, and we show that we can achieve up to 8.8× faster data ingestion with competitive read query performance leading to performance benefits of up to 5× in mixed read/write workloads.
- The OSM meta-design provides the foundation needed to capture a varying degree of data pre-sortedness for tree indexes.

2 PROBLEM STATEMENT

Both indexing and sorting pay the cost to add structure to the data to facilitate faster queries. Both assume that the data is not sorted and that the desired state if fully sorted. Do we need to pay the same cost (of sorting or indexing) for near-sorted data?

**Challenge: Handling Variable Degrees of Sortedness.**
The ingestion complexity for an entry in a $B^+$-tree is $O(\log_e(N))$, irrespective of the order of ingested data. Although this is beneficial in the worst-case when incoming data is completely scrambled, such performance is suboptimal even when some amount of data sortedness exists. Not only do $B^+$-trees do more work, but also carry their worst space amplification for fully sorted inserts. Insertions, in this case, are right-deep, while both the internal and leaf nodes are split in half, leaving 50% of all index nodes unused. The $B^+$-tree and other popular modern indexes are not designed to identify data sortedness to do less work and improve insert efficiency.

**Goal:** We set out to design an index that offers better ingestion performance for higher data sortedness, without hurting the performance of read queries.

### 3 DESIGN ELEMENTS

We now present the four fundamental design elements which, when appropriately combined, allow us to exploit data sortedness. The first three: (i) right-most leaf insertions, (ii) bulk loading, and (iii) fill/split factor adjustment, benefit as-is a fully sorted data ingestion, and when combined with (iv) buffering, can lead to a design that can exploit variable data sortedness. We discuss the key ideas behind the four design elements and, later in Section 4, we discuss how to put them together. We illustrate these ideas in Figure 3.

**Right-Most Leaf Insertion.** When inserting data that follow the order of the index-attribute, we can avoid the logarithmic tree traversal cost by always maintaining a pointer to the right-most leaf node, as shown in Figure 3(a). That way, for every new insert, we first check that indeed it should be directed to the right-most leaf (that is, that the inserted key is larger than the minimum value of that leaf), and we can simply insert it in the leaf. Note that this approach can also absorb a very small degree of sortedness if the size of a leaf node is large enough. In terms of insertion performance, in-order insertion allows us to have a $O(1)$ insertion cost instead of $O(\log_e(N))$. In-order insertion can fall-back to classical insert from the root, which we term top-inserts, when the leaf node is not enough to capture the sortedness.

**Bulk Loading.** If the data is fully sorted, we can perform better than in-order insertion, by bulk loading the data [16], as shown in Figure 3(b). That way, we can avoid accessing a node for every entry. Instead, we append to an in-memory buffer as data arrive, and once a page is full, we create a new right-most leaf. This amortizes the insertion cost across $F$ entries. While bulk loading gives great index creation time if data is fully sorted, it cannot exploit a varying degree of sortedness.

**Fill Factor/Split Factor Adjustment.** When employing any of the above two techniques, we can further optimize the shape of the tree by carefully deciding how we split internal nodes and leaf nodes. Specifically, if the data is fully sorted, the classical split algorithm will create half-full nodes which will never receive any future inserts. Hence, the nodes always remain half-full leading the worst-case with respect to the index space amplification and, in some cases, affecting the index height as well, since the effective fanout will also be half of the nominal one. Instead, if we anticipate data to arrive fully sorted (or as near-sorted as we discuss in the next section), we can decide to employ a different split factor where, for example, 80% of the entries would stay on the original node and the newly created one will only hold 20% of the data in anticipation of the new – higher in terms of value – keys, as shown in Figure 3(c). By changing the split factor, we also allow the nodes to have a higher fill factor on average. The split factor change reduces the number of overall splits needed, improving the insertion performance. The resulting higher fill factor throughout the tree reduces the overall number of nodes needed to hold the data which, in turn, reduces the memory footprint of the data structure.

**Buffering.** The above techniques do not offer substantial benefits if the data is not fully sorted. To utilize these techniques for data with a varying degree of sortedness, we need to buffer incoming data to propagate to the tree only those inserts that are in-order. The buffer is periodically sorted as new entries arrive, to make the first part eligible for bulk loading. In the next section, we discuss how we do this without employing expensive in-memory sorting, and ultimately, without hurting reads that may have to access the in-memory buffer to find the requested values.

### 4 OSM-TREE DESIGN

In this section, we present a new meta-index design that can exploit data sortedness to accelerate ingestion. Section 4.1 presents the preliminary design that puts together the three fundamental design elements from Section 3. In Section 4.2, we augment this design to improve its lookup performance, and finally, in Section 4.3, we put everything together to present our novel OSM-tree design.

#### 4.1 Sortedness-Aware Ingestion

While right-most leaf insertion and bulk loading can help when the data is fully sorted, any degree of sortedness essentially would need a staging area. Hence, we employ a dedicated in-memory insertion buffer which intercepts all index inserts to facilitate future bulk ingestion. Specifically, the buffer allows bulk loading of multiple
data pages into the tree at a constant cost. We now describe the buffering mechanism in detail.

**Basic Structure.** We assume a state-of-the-art tree index like the B\textsuperscript{*} -tree in Figure 4. Note that any variation of B\textsuperscript{*} -tree that supports bulk loading can be part of this meta-design. On top of the basic index, our design includes a buffer that receives incoming data.

**The OSM-buffer.** The in-memory buffer, termed OSM-buffer, maintains all recently inserted data and checks whether the entries are inserted in order. In general, the data in the buffer is eventually inserted into the index either through bulk loading, when possible (that is, when the buffered data have higher values than the data already in the index) or through traditional inserts from the root node (termed top-inserts). By having this design, we can already guarantee that if data is inserted in order, they will be efficiently bulk loaded. We now discuss the buffer flushing strategies that optimize data insertion in the presence of varying degree of sortedness.

**Flush Strategy.** When the buffer becomes full, we flush the buffer to the tree. This flushing can happen either in the form of bulk loading or in the form of top-inserts. Our goal is to maximize the amount of data inserted into the index via bulk loading. In the best case – i.e., when the buffer is fully sorted by virtue of the pre-existing data sortedness – we bulk load the contents of the buffer with no sorting effort. In general, the buffer may not be fully sorted, and we would need to sort it before flushing. At this point, we either (i) bulk load as many pages as possible, if the tree has strictly smaller values than what the (now sorted) buffer has, and (ii) perform top-inserts if there is overlap. Note, that when we perform top-inserts, after inserting a page worth of data, we re-check for overlap, and if possible, revert to bulk loading.

Another decision we make at every flush cycle (i.e., every time the buffer is full) is what portion of the buffer to flush. The insight here is that if we flush the entire buffer, we may insert to the index, entries that overlap with future inserts if the data is anything but fully sorted. Hence, instead of flushing the entire buffer at every cycle, we flush a portion of the buffer (by default, half of it). Partially retaining entries in the buffer after a flush operation helps capture overlaps with future insertions to some extent, which, in turn, increases the number of bulk loaded pages (and decreases top-inserts) across flush cycles. Note that every top-insert costs $O(\log F(N))$ while bulk loading costs $O(1/F)$ since $F$ inserts are serviced by a single node addition.

**Zonemaps to Identify Overlaps.** Our design targets ingestion of near-sorted data. In this case, out-of-order entries are likely to be displaced by a few pages from their ideal position. After a flush cycle, the buffer is half full, and its contents are fully sorted. As a result, no entries are out of order in the buffer, and we mark the last page containing sorted data as the last\_sorted\_zone (Figure 5(a)). Note that every buffer page is treated as a separate zone. As new entries arrive, because of the potential displacement, a newly appended entry may be either (i) overlapping with data in earlier pages, hence moving the last\_sorted\_zone to the left (Figure 5(b)), (ii) overlapping without having to move the last\_sorted\_zone (Figure 5(c)), or (iii) strictly greater, thus moving the last\_sorted\_zone to the right (Figure 5(d)). To update the last\_sorted\_zone, we also maintain Zonemaps per page that allow for a quick overlap test after every insertion. Maintaining the last\_sorted\_zone accurately, helps to avoid unnecessary sorting at every flush cycle.

When the buffer becomes full, we use the last\_sorted\_zone to decide how much to flush. If the most recent entries have moved the last\_sorted\_zone to correspond to less than half of the buffer, we flush only the pages up to the last\_sorted\_zone and attempt to bulk load, if possible. That way, we avoid the sorting cost before flushing. At the same time, the rest of the pages are sorted and moved towards the left to make space for new inserts.

### 4.2 Optimizing Read Queries

While flushing the OSM-buffer helps to harness the sortedness by increasing the fraction of inserts that are bulk loaded, it has an adverse impact on read performance. Specifically, every query goes through the following steps: (i) search the buffer that may contain a sorted part and an unsorted part, and (ii) perform a tree search. In the worst-case, a read query will need a full scan of the buffer. We now discuss how to reduce the cost of a lookup aiming to make it as close as possible to that of the underlying tree.

**Scanning the Unsorted Section First.** In steady-state, the OSM-buffer can be in one of two states: (i) fully sorted or (ii) it can have a sorted portion and an unsorted portion. Note that even if the last\_sorted\_zone is moved to the beginning of the buffer, we still have half of the buffer sorted. So, for any search query, we only need to scan the unsorted portion of the buffer that contains the most recent data. If the lookup key is not found in this part of the buffer, we continue to efficiently search the sorted section of the buffer, and if the lookup has still not terminated, we search the tree. Note that if the key is found in the buffer, we can terminate and avoid searching the tree, as this will be the most recent version of the key. The lifecycle of a query is shown in Figure 6.
**A BF to Skip the Unsorted Section.** The unsorted section is up to half of the OSM-buffer and, thus, holds a small fraction of the overall data (residing in the buffer and the tree). As a result, most queries will not find the desired key in it. Hence, to avoid the cost of unnecessary scanning the unsorted section, we employ a BF that is continuously updated as new entries are inserted. This drastically reduces the cost of queries that do not terminate in the unsorted section.

**Using Zonemaps to Skip Pages in the Unsorted Section.** When the BF returns a positive result, all pages of the unsorted section are marked for scanning. However, we can skip many unnecessary page accesses using the Zonemaps that are already part of the OSM-buffer (used to identify the last_sorted_zone).

**Using Per-Page BF.** While the BF mentioned above and the Zonemaps help avoid many unnecessary accesses, they are not enough if the data is scrambled. Hence, we also maintain a BF per page, which is updated as data is appended to the buffer. Overall, a query starts searching in the unsorted section by first visiting the global BF (with respect to the unsorted section). As shown in Figure 7 for a search query on key 1400, if the BF returns a positive result, we access all Zonemaps to find which pages contain the key in question. Subsequently, for the Zonemaps that contain the key, we probe the per-page BF, and we visit only the qualifying pages.

**Interpolation Search to Search Sorted Section.** After searching the unsorted part of the buffer is complete, if the query has not yet terminated, it will search the sorted section. Note that after every flush the retained data is sorted. Irrespective to whether the newly inserted data overlap with the sorted section (and, thus, move the last_sorted_zone), the data retained after the previous flush remain sorted, and we maintain the position in the buffer until which the data is in sorted order, as previous_boundary. While the last_sorted_zone may move to the left as new entries are inserted into the buffer, the previous_boundary may only move rightwards as long as entries are inserted in fully sorted order, and until the first out of order entry is inserted. Since the sorted section of the buffer is a contiguous sorted array, we employ interpolation search [34, 41] which finishes in $O(\log(\log(N)))$ steps, a notable upgrade from the binary search and is efficient unless there is very high data skew, in which case simply binary search or a variation of exponential sorting [7] can also be employed.

**An Optimized Read Query.** Putting it all together, we have now an optimized read query path that avoids the vast majority of unnecessary data accesses. As Figure 6 shows, we maintain two more

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**4.3 Fine-tuning OSM-tree**

In the previous two subsections, we put together a new meta-design that absorbs inserts faster if they come as near-sorted. Our design further keeps the read query cost close to the cost of the underlying tree. This new meta-design, however, introduces new components and a few tuning knobs that can be further tuned. We begin by the fill and split factors and the choice of sorting algorithms that affect mostly the insertion latency, and we then discuss query-driven sorting to adaptively accelerate read queries.

**Adjusting Fill & Split Factor.** The textbook bulk loading algorithms used in Section 4.1 fills every node with the bulk loaded data to maximize node utilization (and, thus, minimize space amplification). Since we anticipate several of top-inserts (the fraction of which depends on the sortedness of the workload), we also leave in every bulk loaded node several empty slots to facilitate top-inserts without expensive cascading splits. Hence, we adjust the fill factor of every bulk loaded leaf to be 95%.

Similarly, in the textbook insertion and bulk loading, when an internal node is full it splits right in the middle to generate two half-full internal nodes. Since during bulk loading, we anticipate that most of the future inserts will be of larger values, we also adjust the split factor to 80%, as shown earlier in Figure 3(c). This allows us to maintain most of the internal nodes of the underlying tree nearly full, even when the data is coming fully sorted, and essentially avoid the worst-case space amplification of $B^+$-trees for sorted data. In addition to reducing space amplification, we also reduce the total number of node splits, leading to lower overall insertion cost.

**Choice of Sorting Algorithm.** To reduce the cost of read queries, we sort the buffer after every flush making sorting small data collections a very frequent operation. We consider three algorithms: (i) quicksort, because it is the most common algorithm and has minimal space requirements, (ii) $(K, L)$-adaptive sorting [6], because
We set a threshold of how large we allow the unsorted portion $O_L < \text{representations of keys}. However, the OSM-design paradigm and $L$-adaptive sorting. Our analysis shows that for low data-sortedness mergesort outperforms $(K, L)$-adaptive sorting (in fact, $(K, L)$-adaptive sorting fails for very high values of $K$ or $L$). However, for $K < 10\%$ or $L < 5\%$, their performance is similar and we opt for $(K, L)$-adaptive sorting because it has smaller space requirements ($K + L < n$). In summary, when the estimated values of $K$ and $L$ are $K < 10\%$ or $L < 5\%$ of the buffer size we employ $(K, L)$-adaptive sorting, and otherwise mergesort, and specifically the C++ standard library implementation of std::stable_sort.

**Query-Driven Sorted Components.** In our current design, only the first part of the buffer that is sorted can benefit from interpolation search. An additional read optimization is to adaptively add structure to the unsorted part of the buffer with incoming queries. We set a threshold of how large we allow the unsorted portion of the buffer to be (unsorted_threshold). When the threshold is exceeded, the next read query will sort this portion and create a new sorted component. Similar to progressive indexing [22] that allocates a small indexing budget for every query, we allocate a small sorting budget for every query as long as we have enough entries in the unsorted component. In the general case, the OSM-buffer may contain the main sorted section, multiple sorted components of size equal to unsorted_threshold, and a small unsorted section. For example, if the unsorted_threshold is $10\%$ of the buffer size, the buffer will contain five sorted runs (the sorted section and four sorted components) and one unsorted section. The unsorted section still uses all the metadata discussed in §4.2 and each sorted component employs interpolation search to accelerate queries.

**OSM-buffer Size.** The final tuning knob is the size of the OSM-buffer. The goal is to have a large enough buffer that can capture sortedness, focusing on $L$, i.e., the maximum displacement from the expected position. On the other hand, a large buffer would negate any optimization for read queries since the cost of scanning the unsorted part will dominate. In Section 6, we vary the buffer size and the relative values of $K$ and $L$, and we show that even with a buffer significantly smaller than $L$ we can absorb sortedness to a large degree, without hurting read queries.

**4.4 Discussion**

**Handling Strings.** Near-sortedness manifests typically through integers than any other data type, thus, our work focuses on integer representations of keys. However, the OSM-design paradigm and OSM-tree can be extended to other data formats such as strings. Specifically, to address storage constraints, strings with variable sizes can be mapped to fixed-length representations using a dictionary. This accommodates all strings regardless of length. Subsequently, the fixed-length representations can be binary encoded before insertion into the index. We can ensure that the order is preserved through the mapping and the encoding steps. We aim to extend this work and further include a study over near-sorted strings including designing a synthetic workload generator for near-sorted strings, which to our knowledge has been unexplored.

**Learned Indexes.** Contrary to traditional index data structures, learned indexes, use machine learning to learn a model reflecting patterns in the data and enable automatic synthesis of indexes at a low engineering cost [26]. Lookups in learned indexes avoid expensive tree traversals, aiming to offer lower access latency. However, existing learned index proposals require trading workload generality for accuracy. Specifically, to achieve sufficient lookup accuracy, learned indexes make the assumption of completely sorted keys, thus, depend on prior knowledge of the data. OSM-tree addresses the cost of tree traversal by adapting operations to the data. By taking advantage of inherent sortedness, OSM-tree significantly reduces the ingestion cost while offering low latency and full accuracy. As future work, we further aim to extend existing learned indexes to make them sortedness-aware and relax the assumptions regarding input data.

**5 DATA SORTEDNESS BENCHMARK**

We present the data sortedness benchmark for testing indexes against varying sortedness. The benchmark uses the $(K, L)$-near sorted metric (discussed in §2) and is used in our evaluation (§6).

**Benchmark Data.** The benchmark creates a family of differently sorted collections that vary in both $K$ and $L$ (as a fraction of the total data size). These metrics effectively capture sortedness by representing how many entries are out-of-order and how far apart are the entries from their actual position, underlining the effort it would take to establish order in the data collection. When $K = 0\%$ or $L = 0\%$ the dataset is fully sorted. A dataset with $K = 10\%$ and $L = 2\%$ will have $10\%$ of the total entries out of order, each placed within a distance of $2\%$ of the total entries from its in-order position. Figure 9 shows a sample set of differently sorted collections. The x-axis denotes the position of the entry in a data collection and the y-axis represents the value of the entry. The band across every illustration highlights the $L$-window through which elements can
be shuffled. As this window grows, the band increases in width, meaning elements may be further apart from their ideal positions.

**Evaluation Metrics.** The sortedness benchmark evaluates the performance of a data structure in the presence of variable sortedness by measuring: (i) ingestion performance, (ii) overall performance of a mixed workload with variable read/write ratio. The default settings for the benchmark include comparison with multiple L-windows (1%, 5%, 10%, 25%, 50%), and various K values for each window (0%, 1%, 5%, 10%, 15%, 25%, 50%).

**Ingestion Speedup.** This metric quantifies the benefit in terms of ingestion latency by comparing the underlying index with its OSM counterpart. The benchmark reports both raw performance numbers and the speedup that quantifies the ingestion benefit.

**Overall Speedup.** This metric quantifies the benefit when running a mixed workload with a varying degree of insert-to-lookup ratio between 10%-90% and 90%-10%. The benchmark reports raw performance and the overall speedup when comparing the underlying index with its OSM counterpart.

**Microbenchmark Varying K and L.** The above measurements are taken for fixed value of K and L. The last set of measurements of the sortedness benchmark vary both K and L within a window in order to capture their impact. The reported values are raw performance and speedup as well.

### 6 EXPERIMENTAL EVALUATION

We now present the experimental evaluation of OSM-tree.

**Experimental Setup.** We run the experiments in our in-house server equipped with two sockets each with an Intel Xeon Gold 5230 2.1GHz processor with 20 cores and virtualization enabled. The server has 384GB of RDIMM main memory at 2933 MHz with 27.5MB L3 cache and a 240GB SSD. The machine runs on CentOS 8.

**Index Design.** We use a state-of-the-art B+-tree implementation [8] and build on top of it to add support for in-order bulk insertion. Our B+-tree implementation is equipped with a bufferpool of 300GB, so all our experiments are purely in-memory. Note that the bufferpool is orthogonal to the OSM-buffer, which does not have a disk-resident counterpart. The indexed key and payload, unless otherwise noted, is 8B in total, with keys and values of 4B each, and by default, we use 4KB index pages.

**Default Setup.** The default size of the OSM-buffer is 40MB which can hold up to 5M entries. The OSM-buffer is essentially a dense array accompanied by the Zonemaps and Bloom filters as discussed in Section 4. For the BFs, we use 10 bits-per-entry and maintain the filters at two granularities: (i) one for the entire OSM-buffer and (ii) one for each page in the OSM-buffer. The BFs use MurmurHash [3] for hashing, following the state-of-the-art [42].

**Workload.** Given the lack of sortedness benchmarks, we create our custom workload generator based on the (K, L)-nearly sorted metric [6] to generate workloads with varying degrees of sortedness as discussed in Section 5. Unless otherwise mentioned, the ingestion workload consists of 500M key-value entries with a total size of 4GB, and the query workload has a variable number of uniform random non-empty point lookups, interleaved with inserts after 80% of the ingestion is complete.

![Figure 10: OSM-tree (Buffer size=5M) is efficient with reasonable data sortedness for any read-write ratio.](image)

**OSM Tuning.** Unless otherwise mentioned, we tune our OSM-tree as follows. The OSM-buffer flushes 50% of the entries when saturated. The nodes split as 80:20 between the left and right one, and the in-order bulk insertion fills every leaf up to 95%. For workloads with queries interleaved with inserts, a sorted block is created (triggered by a query) after at least 500K new entries (10% of the buffer capacity) are accumulated.

### 6.1 Mixed Workload

We first compare the performance of OSM-tree with B+-tree by executing a set of mixed workloads with interleaved inserts and queries. We vary the read-write ratio, constructing a continuum between a write-heavy and a read-heavy workload. For each workload, we also vary the sortedness for the ingested data as: (i) fully sorted, (ii) near-sorted (K=5%, L=5%), (iii) less sorted (K=50%, L=50%), and (iv) scrambled (uniformly random). For each experiment, we measure the speedup offered by OSM-tree as speedup = \( \frac{\text{latency}(B^+-\text{tree})}{\text{latency}(\text{OSM-tree})} \), where latency(B+-tree) and latency(OSM-tree) refer to the total workload execution latency of the OSM-tree and B+-tree, respectively.

**OSM-tree Outperforms B+-Tree.** Figure 10 shows that OSM-tree significantly outperforms B+-tree if the data is fully sorted or near-sorted. For an ingestion-heavy workload, OSM-tree leads to 8.8x speedup for fully sorted data and 5x better for near-sorted data in ingestion-heavy workloads. OSM-tree achieves this by buffering entries in-memory to add structure to the data and reduce the number of top-inserts. In the case of fully sorted data, all of the entries are ingested through the bulk insertion, while for the near-sorted data, only ~4% of the entries are top-inserts and the remaining follow bulk insertion. Figure 11 shows that OSM-tree performs significantly fewer top-inserts for workloads with a high degree of sortedness. For fully sorted or nearly sorted workloads (i.e., K or L ≤ 10%), OSM-tree ingests >90% data through bulk loading, and thereby, reduces the overall cost for ingestion. As data becomes less sorted, OSM-tree mimics the behavior of a B+-tree. This is
because, as the degree of data sortedness decreases, OSM-tree’s ability to capture the out-of-order elements using a relatively small buffer (1% of data size) diminishes, and the number of top-inserts performed becomes comparable to that of a B+-tree.

Regardless of data sortedness, the benefit of OSM-tree is more pronounced for write-intensive workloads. Conversely, in Figure 10 we observe that for a lookup-heavy workload (90% lookups), OSM-tree offers a speedup of 1.4× and 1.3× for fully sorted and nearly sorted data, respectively. This is because the significant performance benefits of OSM-tree during ingestion are countered by the lookup overhead incurred.

**Ingesting Scrambled Data Does Not Benefit from OSM-tree.** When the ingestion is scrambled, OSM-tree does not offer performance benefits. Specifically, when the data is generated uniformly random, using a B+-tree is about 20% faster than OSM-tree, regardless of the proportion of ingestion and lookups in a workload. This is attributed to the fact that a finite buffer is unable to capture the (minimal) sortedness of the incoming data. This, in turn, forces OSM-tree to always perform top-inserts. For that reason, the OSM buffer management cost (sorting the buffer, managing metadata, and probing BFs during lookups) does not pay off, however, it keeps the penalty to a modest 20%. This observation is inline with our goals and our expectation. While OSM-tree is very useful for a varying degree of sortedness, for fully scrambled data, the worst-case guarantees of a classical B+-tree are enough.

**OSM-tree Reduces Memory Footprint for High Data Sortedness.** The memory footprint of OSM-tree is 0.52× (0.6x) of the size of a B+-tree for fully sorted (near-sorted) data as shown in Table 1. The gain in memory footprint is attributed to the 80:20 split ratio of OSM-tree nodes, which achieves higher fill factor for high data sortedness. On the other hand, for less-sorted data the 80:20 split ratio does not offer any benefit.

### 6.2 Raw Performance

Next, we compare the OSM-tree and B+-tree in terms of ingestion and query performance separately. We vary the number of out-of-order entries (K%) in the ingestion workload, while keeping the maximum displacement of an out-of-order entry (L%) constant. We keep L constant because capturing the degree of sortedness with different L values requires changing the buffer size as a function of L. In Sections 6.3 and 6.4, we discuss the implications on performance of varying both K, L as well as the buffer size.

### Setup

To measure the raw ingestion performance, we first ingest 500M entries (4GB), and for the query performance, we perform 50M (10%) lookups on the inserted keys. We report the worst-case lookup performance, by making sure that the buffer is full before executing any query. To analyze the range scan performance, we execute 100 range scans generated randomly from the key-domain on a preloaded database for different scan-selectivities.

| Sortedness Degree | # Nodes (#Int + #Leaf) |
|-------------------|------------------------|
| Fully-Sorted      | 2.064M (8K, 1.996M)    |
| Near-Sorted       | 1.847M (7K, 1.840M)    |
| Less-Sorted       | 1.878M (4.3K, 1.873M)  |

### OSM-tree Dominates the Ingestion Performance

Figure 12(a) shows that OSM-tree performs significantly better than B+-tree for inserts if there is any degree of data sortedness. For fully sorted (K=0%) and nearly sorted (K=1%, 5%, and 10%) workloads, OSM-tree reduces the ingestion latency by ∼90% and ∼82%, respectively. Even for data with lower degrees of sortedness (K=25% and 50%), the ingestion latency in OSM-tree is reduced by ∼27% compared to B+-tree. Figure 13(a) shows the breakdown of the ingestion costs in OSM-tree for (i) fully sorted (K=0%), (ii) nearly sorted (K=L=5%), and less sorted (K=L=50%) workloads. We observe that for fully sorted workloads, the OSM-tree is able to bulk load the entire data set without requiring any additional processing. For near-sorted data, OSM-tree sorts the buffer periodically (driven by the queries and the buffer-saturation) which accounts for 38% of the workload execution latency. However, this additional cost paid to add structure to the data leads to significantly fewer top-inserts, which in turn, reduces the overall latency. Finally, for less sorted data, OSM-tree ingests fewer entries via bulk loading. Instead, a significant amount of data is ingested through top-inserts – this behavior resembles the one of a B+-tree. However, as shown in Figure 10, OSM-tree still outperforms the state of the art by a significant margin. Note that OSM-tree achieves this performance with a buffer that is 20% in size when compared to L (1% vs. 5%). This implies that even with a considerably small buffer that does not capture the out-of-order elements, OSM-tree performs significantly fewer top-inserts and is able to bulk load a large fraction of the data.

### Fast Ingestion Comes at a Small Overhead in Queries

Figure 12(b) compares the point lookup performance of OSM-tree to
that of the B*-tree, and we observe that OSM-tree incurs an overhead between ~5% and ~26% for point lookups. This is due to the additional time spent searching for the target entry in the buffer. Figure 13(b) shows the breakdown of the point query latency in OSM-tree for (i) fully sorted ($K=0$%), (ii) nearly sorted ($K=L=5$%), and less sorted ($K=L=50$%) workloads. We observe that regardless of the degree of data sortedness, between 80% and 99% of the query latency comes from the tree-search. With a full buffer, OSM-tree introduces an overhead due to (i) probing the OSM-buffer using interpolation search and sequential scans and (ii) performing OSM-operations such as sort-merging the entries in buffer and updating the metadata. This overhead depends on the number of entries in the buffer and degree of data sortedness. Note that for fair comparison, we assumed the buffer to be completely full when the query workload was executed. In practice, the buffer is expected to be 50% saturated on average, which would reduce the buffer-related overheads by $2\times$. Further, searching within the buffer and in the tree in parallel can reduce OSM-tree’s lookup cost.

**The Benefits Outweigh the Overhead almost Always.** To weigh the benefits of OSM-tree against its read overhead, in Figure 12(c), we show the mean latency per operation for a mixed workload. We observe that for a workload with equal number of reads and writes, OSM-tree improves the mean latency by ~70% for fully and nearly sorted data. Even for workloads with larger degrees of sortedness, OSM-tree offers 1.25× improved overall performance. To summarize, for read-only workloads, the performance of OSM-tree is similar to that of B*-trees, as the buffer remains empty, and thus, adds no overhead. However, if a mixed workload is read-dominated (writes < 1%), the incurred read overhead out-weighs the benefits on ingestion of OSM-tree. We present a detailed account of the applicability of OSM-tree in Section 6.3.

**OSM-Tree Offers Competitive Scan Performance.** Figure 12(d) shows that OSM-tree performs similarly to B*-trees for range queries with different selectivity, varying from 0.01% (50 entries) to 1% (5M entries). We observe that scan latency for OSM-tree and B*-tree remain largely comparable while the selectivity is varied. This is because the scan latency is directly proportional to selectivity, and with a tree of the same height, the tree-traversal and leaf node scan costs are similar for both systems. For OSM-tree, the tree search latency dominates the scan time of the OSM-buffer, which can be further reduced by parallelizing it with the tree search and sort-merging the result sets.

### 6.3 Workload Influence

**Setup.** We measure the speedup offered by OSM-tree over state-of-the-art B*-trees for mixed workloads with varying data sortedness. We vary both $K=(0, 1, 5, 10, 50)$ and $L=(1, 5, 10, 50)$ and experiment with 20 different degrees of data sortedness.

**Varying the Workload Composition.** We observe in Figures 14(a)-14(c) that as the proportion of reads increases in a workload (from 10% to 50% to 90%), the overhead incurred by reads in OSM-tree begins to counterbalance its ingestion-benefits. Even for a fully sorted workload, as the read-proportion increases from 10% to 90%, the speedup is reduced from 9.2× to 1.4×. Thus, for different degrees of data sortedness, Figure 14 serve as a guideline for the applicability of the OSM-tree design.

**Varying the Degree of Sortedness.** Analyzing the variation in the speedup for $K=1\%$ (second column) and $L=1\%$ (fifth column) in Figure 14(a), we observe that the effects on the number of unordered entries in the workload (i.e., $K$) influences the performance of OSM-tree by a greater extent compared to the maximum displacement of an unordered element (i.e., $L$). This is because if the buffer size is comparable to the $L$-value, the number of unordered entries drive the cost of data reordering, and relative overlaps between buffer cycles (causing top-inserts) is minimal. However, as $L$ gets larger (first row), its impact on the speedup becomes more significant than that of $K$ (fifth column). With increase in both $K$ and $L$, the OSM-tree begins to operate similarly to B*-trees, and the speedup offered approaches 1.

### 6.4 OSM-buffer Tuning

**Setup.** To analyze the implications of buffer size on OSM-tree’s performance, we first increase the buffer size to 5% of the data size and compare the results with those discussed in Section 6.2. Next, we run an ingestion-only workload with 500M entries followed by a read-only workload with 50M point lookups, and we vary the buffer size between 0.5%-5% of the data size. For mixed workload, we pre-load the index (to 80%) and perform interleaved inserts and reads (50%W-50%R) for different degrees of sortedness.

**Increasing the Buffer Size Improves Performance.** We now vary the size of the OSM-buffer to show its implications on performance. The OSM-buffer acts as a reservoir that absorbs the out-of-order ingested elements to an extent. Thus, increasing the buffer size allows for bulk loading a larger fraction on the data while reducing the number of top-inserts. Figure 14(d) shows the speedup offered by OSM-tree when OSM-buffer size is increased to 5% of the data size (200MB) for a mixed workload with equal proportions of reads and writes. Comparing with Figure 14(b) (which has the same setup but a buffer size of 1%), we observe that a 5× increase in the buffer size increases the speedup from 4.2× to 8.2× (a 95.2% increase) for a fully sorted workload and between 27.6% and 176.9% for nearly sorted data. Even for $K=L=50\%$, increasing the buffer size improves the achieves speedup from 1× to 1.3×.

**Buffer Size Affects the Ingestion Performance Significantly.** Figure 15 shows the implications of varying buffer size separately on the ingestion and lookup performance for OSM-tree. In this set of experiments, we vary the OSM-buffer size for a fixed sortedness ($K = L = 5\%$). We observe that even with a small buffer size of 20MB (0.5% of the data size), OSM-tree offers...
Figure 14: Performance of OSM-tree with varying degrees of sortedness. (a) In a write-heavy workload, OSM-tree exploits data sortedness to offer maximum benefit in overall performance. (b) Increase in reads to the index diminishes the benefit offered by OSM-tree. (c) OSM-tree performs similar to B*-tree for read-heavy workloads with minimal performance benefits due to data sortedness. (d) A larger buffer in OSM-tree is better at capturing even higher sortedness, to improve overall performance.

Figure 15: The ingestion performance of OSM-tree increases proportionally with buffer size.

Figure 16: Query-based sorting threshold set to 10% offers the highest speedup.

Figure 17: Latency breakdown for different OSM-tree configurations. (a) Adding BFs to the OSM-buffer slightly increases the insert latency. (b) The use of BFs in the buffer for lookups is more pronounced as data sortedness decreases.

We now vary the proportion of entries flushed from the buffer at a time.

Adjusting the flush threshold:

Figure 18: Latency per Insert (µs) (a) Naïve OSM, OSM-Global BF, Full OSM

Figure 19: Latency per Lookup (µs)

A 10x increase in the buffer size (from 20MB to 200MB) induces a deterioration of 11.5% in the lookup latency. This conforms with our observations from Figures 12(b) and 14(c) regarding the suitability of the OSM-design; however, as shown in Figure 10 the benefits on OSM-tree outweigh the read-overheads even for a small fraction of writes (≥5%).

The Buffer Flush Threshold. Adjusting the flush threshold of the OSM-buffer affects the overall performance of OSM-tree. We now vary the proportion of entries flushed from the buffer at a given cycle between 25%, 50%, and 75%, and run mixed workloads. In the interest of space, we omit the figure and focus on the key observation. When the buffer flush threshold is set to 25%, OSM-tree offers a speedup between 1.0x and 4.0x. For flush threshold 50%, the speedup of OSM-tree becomes between 1.0x and 4.3x, and for a threshold of 75%, between 0.91x and 4.2x. Hence, OSM-tree performs best for 50% flush threshold, which we default to.

Tuning Query-Based Sorting. Figure 16 shows the implications of query-based sorting on the overall performance of OSM-tree. We vary the query-based sorting threshold between 1%, 5%, 10%, 25% and 100% (disabling query-based sorting) and run mixed workloads. The y-axis shows the speedup when compared against our B*-tree baseline. We observe that enabling query-based sorting offers a performance improvement between 7% (for 1% threshold) and 25% (for 10% threshold). As expected by gradually sorting the buffered data significantly accelerates query performance on average since the portion the buffer that needs to be scanned is kept small. Moreover, we observe that query-based sorting has diminishing returns if we apply it too frequently. Specifically, setting the threshold to 10% offers the maximum speedup for any data sortedness, while other values affect performance adversely (if at all). Reducing the threshold (to 1% or 5%) leads to too much sorting, while increasing the threshold (to 25%) results in fewer sorted blocks within the buffer, so the cost of scanning the unsorted section remains high. Hence, we empirically tune OSM-tree to perform query-based sorting with threshold 10%.

Benefits from the Global and Per-page BFs. To demonstrate the benefits coming from the global BF and from the per-page BFs in the OSM-buffer we compare OSM-tree with two simpler variations: one without any BFs (Naïve OSM) and one with only the global BF (OSM-Global BF) by ingesting 500M near-sorted entries and then performing 50M non-empty point lookups. As expected, updating the BFs during every insertion comes at a marginal cost increase at ingestion time as shown in Figure 17(a). For less sorted data the added cost at ingestion time is a smaller fraction of the total insert time. However, the additional cost at ingestion time pays off since at query time we have significant performance benefits. Figure 17(b) shows that adding the global BF speeds up queries up to 14%, while the per-page BFs further boost performance leading to 16% aggregate improvement. The positive impact of per-page BFs is limited by query-based sorting that also helps avoid scanning unnecessary data (limiting the portion of OSM-buffer to be scanned to <10%). Note that the ingestion performance of OSM-tree is always
significantly faster than B$^+\text{-tree}$ regardless of the BF cost. Overall, the benefit of BFs is pronounced for workloads with more reads.

**Tuning Zonemaps.** OSM-buffer uses Zonemaps during ingestion to approximate sortedness (§4.1) making them integral to the overall design. While we opt to always use them at query time since they are always available, we experimentally measured that skipping Zonemaps at query time reduces performance by 35% on average.

### 6.5 On-Disk Performance

In our next experiment, we explore an OSM-tree setup that accesses disk-resident data. Our design comes with a bufferpool that, in this experiment, fits all internal tree nodes (~1% of data size). We repeat the initial experiment for variable data sortedness and variable read vs. write ratio, to present the speedup between OSM-tree and B$^+\text{-tree}$ as shown in Figure 18. Note that the OSM-buffer is set to 1% of the total data. From the disk-based experiment we draw similar conclusions to the initial in-memory one (Fig. 10), with a notable difference. OSM-tree now always outperforms B$^+\text{-tree}$ even for read-intensive workloads with fully scrambled data. This is because, regardless of data sortedness, we increase locality through our sorting procedures in the buffer. Though this is applicable for both in-memory and disk-based experiments with OSM-tree, the overhead of managing the buffer is negligible when compared to accessing tree nodes for the disk-based experiment. Overall, when spilling to disk, OSM-tree leads to significant performance savings up to 8x for write-intensive workloads with high data sortedness, while always outperforming B$^+\text{-tree}$.

### 6.6 Scalability

**OSM-Tree Scales Similarly to the State of the Art.** To analyze the scalability of OSM-tree, we increase the number of entries ingested from 31.25M to 1B while varying $K$ and $L$ as proportional (5%) to the workload size. We also scale the actual size of OSM-buffer by keeping it equal to 1% of the dataset size. For each experiment, we first ingest 80% of the ingestion workload and then interleave the remaining inserts with equal number of of point lookups. As expected, the degree of data sortedness does not affect the performance of B$^+\text{-trees}$ and the latency per operation remains nearly unaffected by the increase in data size. OSM-tree scales similarly to the state of the art while offering a speedup between 2.32x and 3.14x as shown in Figure 19(a). Increasing the buffer size proportionally with $L$ allows OSM-tree to absorb the same degree of sortedness within the buffer regardless of the buffer size.

### 6.7 Experimenting with TPC-H

Finally, we evaluate OSM-tree by comparing its performance against state-of-the-art B$^+\text{-trees}$ on TPC-H [40] data.

**Setup.** For this experiment, we use the tuples in the lineitem table (as discussed in Section 1) as our workload. We sort the tuples based on the shipdate attribute which, in turn, creates a nearly sorted data set with respect to the receiptdate attribute. We attribute this degree of sortedness on receiptdate as: $K=96.67%$ and $L=0.1%$. The workload is comprised of 6M tuples. For both OSM-tree and the B$^+\text{-tree}$, we first preload the database and the index with 4.8M entries and then execute a mixed workload with varying proportions of reads and writes. We measure the latency per operation during the mixed workload execution and compute the speedup accordingly. For each set of experiment, we also vary the buffer size between 0.05% and 1% of the data size.

**OSM-Tree Offers Superior Performance.** Table 3 shows that OSM-tree performs significantly better than B$^+\text{-trees}$ across all buffer sizes and for all workload compositions. Even with a buffer that is 0.05% of the data size, OSM-tree offers between 1.14x and 1.63x speedup. As the buffer size increases, it is able to cache more entries before flushing, which reduces the number of top-inserts performed, improving ingestion performance. We also observe that the benefits of OSM-tree diminish as the proportion of reads increase in the workload; however, even for a workload with 90% reads,
While to the best of our knowledge, this is the first work on de-
high write amplification cost. Data entries are repeatedly re-written
LSM-trees.

A design paradigm can be adapted to reduce storage overhead and
formance by allowing efficient out-of-order insertions and taking ad-
itions have to be searched. Similarly, B
is known, this leads to efficient execution, otherwise, multiple par-
lapping data. At query time, in case the leading column (e.g., epoch)
always append, which leads to creating multiple indexes on over-
optimizes bulk insertion by using an artificial leading column to
uture that aims to maximize bulk insertion by pushing new inserts
latency. YATS-tree (or Y-tree) [24] is a hierarchical indexing struc-
tures that can benefit from the OSM meta-design to better exploit variable
ortedness. Further, the LSM design per se can be optimized to better
handle sorted data ingestion.

Data Series and Data Streaming. Data series store data with a
monotonically increasing component, typically a timestamp [33].
Data series indexing assumes that data ingestion follows the ex-
pected order [25, 43–45]. The ingested data is converted to shapes
using specialized representations like iSAX [11], in order to allow
similarity comparisons between data series.

Data streaming applications operate on windows of data (typ-
cally time-based) in order to calculate state on-the-fly, and then,
discard the incoming entries [12, 17]. Hence, streaming systems
inspect whether data arrives out of the expected order and often
use a buffer to capture this arrival skew [38]. They do not build an
index for the entire dataset, and similar to data series, the default
 expectation is that data arrives in the expected order.

Contrary to data series and data streaming, in relational systems,
the arrival of data is, in general, scrambled; however, indexes are
not designed to benefit from data arriving in-order or near-order. In
this work, we treat sortedness as a resource, and we build a general
purpose index that can substantially outperform existing indexes if
data ingestion order follows the indexed key, while falling back to
baseline performance if there is no underline data sortedness.

7 RELATED WORK

While to the best of our knowledge, this is the first work on de-
signing sortedness-aware indexes, in this section, we discuss the
literature on ingestion-optimized index structures.

Optimizing for Tree Ingestion. B+-trees are widely used as the
indexing data structure in commercial database systems due to its
balanced ingestion and query performance [14]. Over the past
years, several B+-tree-variants have been proposed that focus on
optimizing ingestion and promote batching. Lehman and Carey
proposed an in-memory tree index, T-tree [27], which improves
insertion and access performance by storing pointers to data in the
nodes. CSB+-tree [36] and PLI-tree [39] attempt to maximize the
cache line utilization by using arithmetic operations to calculate the
child nodes rather than pointer operations to reduce the ingestion
latency. YATS-tree (or Y-tree) [24] is a hierarchical indexing struc-
ture that aims to maximize bulk insertion by pushing new inserts
into separate blocks based on a total order. Partitioned B+-tree [19]
optimizes bulk insertion by using an artificial leading column to
always append, which leads to creating multiple indexes on overlap-
ing data. At query time, in case the leading column (e.g., epoch)
is known, this leads to efficient execution, otherwise, multiple par-
titions have to be searched. Similarly, B+-tree [10] reduces the cost
of trickle insertions by buffering data in internal nodes.

Contrary to OSM-tree, none of the above B+-tree-variants aim to
exploit implicit structure in the ingestion workload. The LSM-tree
design techniques presented in this paper, offer superior perfor-
ance by allowing efficient out-of-order insertions and taking ad-
antage of data sortedness when available. Furthermore, the OSM
design paradigm can be adapted to reduce storage overhead and
ache misses, as well as to reduce the balancing cost.

LSM-trees. LSM-trees [28, 32] optimize data ingestion by buffering
and flushing to disk sorted pages, however, their design comes at a
high write amplification cost. Data entries are repeatedly re-written
on disk, and LSM-trees periodically sort-merge smaller sorted com-
ponents to create larger sorted collections of data through the
process of compactions [37]. While LSM-trees aim to maximize inges-
throughput, they are not designed to exploit sortedness. In
fact, most LSM-tree designs are completely agnostic to data sorted-
ness and they perform the same amount of merging and (re-)writing
of the data on disk even when the data arrive fully sorted.
When an LSM-tree employs a leveled partial compaction strategy with
no-overlap data movement policy [37] it can accelerate ingestion of
sorted data, however, to fully exploit a varying degree of sortedness,
more changes are needed in various compaction decisions. LSM
Can benefit from the OSM meta-design to better exploit variable
ortedness. Further, the LSM design per se can be optimized to better
handle sorted data ingestion.

OSM-tree offers a speedup of 1.3× on average. Interestingly, for
larger proportions of reads (≥75%), a larger buffer size (≥1%) causes
reads to probe more data in the buffer for every lookup, which, in
turn, causes a slight drop in OSM-tree’s speedup. Overall, this ex-
periment highlights that the OSM-design is able to offer significant
performance benefits compared to the state of the art with a very
small buffer size (0.05%) even for workloads with large proportions
of reads (90%) and low degree of data sortedness (K=96.67%).

Table 3: When querying TPC-H data, OSM-tree always out-
performs B+-tree offering speedups between 1.14× and 5.3×.

| Read : Writes | Buffer Size (%data size) |
|--------------|--------------------------|
| 10% : 90%    | 1.63× 2.60× 2.88× 4.46× 5.28× |
| 25% : 75%    | 1.54× 2.40× 2.49× 3.62× 4.57× |
| 50% : 50%    | 1.56× 2.07× 2.82× 3.21× 3.40× |
| 75% : 25%    | 1.25× 1.65× 1.72× 2.09× 2.01× |
| 90% : 10%    | 1.14× 1.24× 1.28× 1.42× 1.41× |

8 CONCLUSION

Inserting data to an index can be perceived as the process of adding
structure to an otherwise unsorted data collection. We identify
herent data sortedness as a resource that should be harnessed
when ingesting data. However, state-of-the-art index designs like
B+-trees can only enable faster ingestion through bulk loading when
data arrives fully sorted, and they fail to benefit from sortedness
when data is near-sorted.

To address this, we propose an index meta-design that allows for
progressively faster ingestion when the incoming data has increas-
ingly higher sortedness. Our proposed design, called OSM-tree,
uses partial bulk loading, index appends, variable split factor, and
in-memory buffering to amortize the insertion cost. OSM-tree also
offers competitive lookup performance by engaging Bloom filters
and Zonemaps for data in the in-memory buffer. Our experiments
demonstrate that OSM-tree outperforms the baseline B+-tree by up
to 8.8× in presence of data sortedness and offers up to 5× perfor-
ance improvement for mixed read/write workloads.
