Fast, Incremental Inverted Indexing in Main Memory for Web-Scale Collections

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ABSTRACT

For text retrieval systems, the assumption that all data structures reside in main memory is increasingly common. In this context, we present a novel incremental inverted indexing algorithm for web-scale collections that directly constructs compressed postings lists in memory. Designing efficient in-memory algorithms requires understanding modern processor architectures and memory hierarchies: in this paper, we explore the issue of postings lists contiguity. Naturally, postings lists that occupy contiguous memory regions are preferred for retrieval, but maintaining contiguity increases complexity and slows indexing. On the other hand, allowing discontiguous index segments simplifies index construction but decreases retrieval performance. Understanding this tradeoff is our main contribution: We find that co-locating small groups of inverted list segments yields query evaluation performance that is statistically indistinguishable from fully-contiguous postings lists. In other words, it is not necessary to lay out in-memory data structures such that all postings for a term are contiguous; we can achieve ideal performance with a relatively small amount of effort.

1. INTRODUCTION

For text retrieval applications today, it is reasonable to assume that all index structures fit in main memory, so that query evaluation can avoid hitting disk altogether. In industry, this is a practical requirement given users’ expectations of low latency responses and the operational demands of high throughput to serve many concurrent users \(^10\). In the academic literature, there has been work on query evaluation using main-memory indexes \(^31\), and the assumption of holding all index structures in memory is now common \(^23\), \(^1\), enabled by the falling prices of hardware. Servers capable of holding web-scale collections in memory are within the reach of most academic researchers today.

In this paper, we explore incremental (sometimes referred to as “online”) inverted indexing algorithms in main memory for modern web-scale collections. Our rationale is that if indexes are going to be served from memory, we should be able to build indexes in memory also, provided that the additional “working space” required by the indexer is modest. We describe a novel indexing algorithm for incrementally building compressed postings lists directly in memory. Of course, incremental indexing is not a new research topic, but most previous work assumes that the index will not fit in memory and must reside on disk. Our assumption puts us in a different, underexplored region of the design space.

Frequently, indexing algorithms encode a tradeoff between indexing and retrieval performance. Our study specifically examines the issue of postings list contiguity, which manifests such a tradeoff. By contiguity we mean whether each postings list occupies a single block of memory or is split into multiple segment placed at different memory locations. Why does contiguity matter? From the retrieval perspective, we would expect an impact on query evaluation speed: traversing postings lists that occupy a contiguous block of memory takes advantage of cache locality and processor prefetching, whereas discontiguous postings lists suffer from cache misses due to pointer chasing. However, from the indexing perspective, maintaining contiguous postings lists introduces substantial complexity, for example, requiring either a two-pass approach, eager over-allocation of memory, or repeatedly copying postings when they grow beyond a certain size. With each of these techniques we would expect indexing performance to suffer. Thus, a faster, simpler indexing algorithm that does not attempt to maintain postings list contiguity may result in slower query evaluation. It is this tradeoff that we seek to understand in more detail.

This paper has two main contribution: First, we present a novel in-memory incremental indexing algorithm with several desirable features: it is fast, scales to modern web-scale collections, and takes advantage of best practice index compression techniques. Second, in the context of this indexing algorithm, we explore the impact of postings lists contiguity on indexing and query evaluation performance (both conjunctive and disjunctive). We find that small discontiguous inverted list segments do indeed cause a drop in query evaluation speed, but that co-locating small groups of index segments yields performance that is statistically indistinguishable from fully-contiguous postings lists (which are difficult to maintain in an online setting). In other words, we can achieve ideal performance with a relatively small amount of effort. This somewhat surprising result is explained in the context of modern processor architectures. To our knowledge, we are the first to explore this issue in the context of main-memory indexes.

2. BACKGROUND AND RELATED WORK

2.1 Processor Architectures

The performance characteristics of rotational magnetic disks (slow seeks but good throughput) is well understood by the IR community, and previous disk-based algorithms are specifically adapted to these characteristics. Memory, however, exhibits a different set of performance characteristics that are less discussed in the community. Therefore, we
begin with a high-level overview of modern processor architectures as it pertains to the algorithms discussed here.

Compared to the multi-core revolution in computing, a less-discussed, but just as important trend over the past two decades is the so-called “memory wall” [3], where increases in processor speed have far outpaced improvements in memory latency. This means that RAM is becoming slower relative to the CPU. In the 1980s, memory latencies were on the order of a few clock cycles; today, it could be several hundred clock cycles. To hide this latency, computer architects have introduced hierarchical cache memories: a typical server today will have L1, L2, and L3 caches between the processor and main memory. The fraction of memory accesses that can be fulfilled by the cache is called the cache hit rate, and data not found in cache is said to cause a cache miss. Cache misses cascade down the hierarchy—if a datum is not found in L1, the processor tries to look for it in L2, then in L3, and finally in main memory (paying an increasing latency cost each level down). The key point is that memory latencies are not uniform, and can actually vary by orders of magnitude (comparing L1 cache hit vs. accessing main memory).

Managing cache content is a complex challenge, but there are two main principles relevant to a software developer. First, caches are organized into cache lines (typically 64 bytes), which is the smallest unit of transfer between cache levels. That is, when a program accesses a particular memory location, the entire cache line is brought into (L1) cache. Subsequent references to nearby memory locations are very fast, and therefore, it is worthwhile to organize data structures to take advantage of this fact. Second, if a program accesses memory in a predictable sequential pattern (called striding), the processor will pre-fetch memory blocks and move them into cache, before the program has explicitly requested the memory locations. This means that predictable memory access patterns (e.g., traversing contiguous postings lists) are critical to high performance.

Another salient property of modern CPUs is pipelining, where instruction execution is split between many stages. At each clock cycle, all instructions “in flight” advance one stage in the pipeline; new instructions enter the pipeline and instructions that leave the pipeline are “retired”. Pipeline stages allow faster clock rates since there is less to do per stage. Modern superscalar CPUs add the ability to dispatch multiple instructions per clock cycle (and out of order) provided that they are independent.

The implication of this is that pointer chasing, which occurs when we try to locate the next segment of a discontinuous postings list, is slow due to what is called a data hazard in VLSI design terminology, when one instruction requires the result of another. When dereferencing pointers, we must first compute the memory location to access. Subsequent instructions cannot proceed until we know what memory location is needed—the processor simply stalls waiting for the result. That is, no dependent instructions can enter the pipeline, and given memory latencies discussed above, this delay can be many cycles. Thus, accessing arbitrary memory locations in RAM is not very efficient—this parallels the relationship between disk seeks and scans, but of course, with a completely different underlying physical model.

In the context of information retrieval, there is one additional complexity worth noting. Following best practice, we use PForDelta [40, 36] for compressing postings lists. Since it is a block-based technique (i.e., integers are coded in groups, typically 128), decompression yields memory access patterns that differ from techniques which code one integer at a time (e.g., variable-length integers, γ codes, etc.). Our experiments show that this has the effect of masking memory latencies and cache misses.

## 2.2 Incremental Indexing

In this paper, we only examine standard inverted indexes—mappings from terms to postings lists, where each posting holds the document id, term frequency, and term positions. We set aside alternatives such as bit signatures [39], recent work on self-indexes [26], as well as the approach of Lempel et al. [17], who eschew inverted indexes completely.

As previously mentioned, most previous work on incremental indexing assumes that postings lists do not fit in memory and ultimately must be organized on disk. The design space of indexing strategies is nicely illustrated by Tomasic et al. [22], who examined the problem of index updates: how to append an in-memory list $M$ to a list $L$ on disk. We summarize only the important results here. Tomasic et al. explored different disk allocation policies: with the constant approach, a constant amount of space is reserved at the end of every list for new postings. In contrast, the proportional strategy reserves empty space at the end proportional to the number of postings being written to disk; thus, longer lists have more room to grow. Complementary to these allocation policies is the update strategy. If the in-memory list to be written fits into the reserved space, then the on-disk list is updated in place. Otherwise, the authors discuss different options: whole, which combines the in-memory and on-disk list and writes the result to a new location, thereby maintaining a contiguous list; and new, which writes the in-memory list to a new location, thus creating a linked list of segments. Not surprisingly, experiments show that the new strategy is quicker for index updates since there is no need to copy data, while the whole strategy is preferred for query evaluation since it reduces the number of disk seeks needed when traversing postings.

Other researchers explored different choices that can be understood in terms of the general strategies described above. For example, Brown et al. [5] proposed allocating space in powers of two, up to a maximum ($2^4, 2^5, ..., 2^{13}$). If there is enough space at the end of the current on-disk list to accommodate the in-memory postings, the in-memory postings are appended in place. Otherwise, a larger chunk is allocated and the contents of the old block are moved to the new one, with the new postings appended to its end. In another work, Shieh and Chung [29] elaborate on over-allocation strategies that take into account different statistics (e.g., space usage and update request rate). One additional finding supported by multiple studies is the importance of separately handling “short” and “long” postings, for example, by storing short postings directly in the dictionary [9] or in “buckets” [30].

After a burst of activity in the early to mid 1990s, there was a lull in work on incremental indexing until a series of papers by Lester et al. [18, 19]. Their basic strategy was to first perform in-memory inversion within a bounded buffer, for example, using the technique of Heinz and Zobel [15]. Inevitably (under the assumptions of limited memory), postings must be flushed to disk. Lester et al. outlined three options for what to do once memory is exhausted: rebuild the index on disk from scratch (not very practical), modify postings in place on disk (practical only for small updates),
or to selectively merge in-memory and on-disk segments and rewrite to another region on disk. In particular, they explored a geometric partitioning and hierarchical merging strategy that limits the number of outstanding partitions, thereby controlling query costs. The same basic idea was described at around the same time by Büttcher et al. [7], who called their approach “logarithmic merge”. Both approaches were subsequently generalized by Guo et al. [13], who introduced a method to dynamically adjust the sequence of segment merges. Recently, researchers have applied some of these techniques to solid state disks (SSDs) [21], which manifest performance characteristics that are different from both RAM and disk; however, a full discussion of SSDs is beyond the scope of this work.

Using the basic buffer-and-flush approach, Margaritis and Anastasiadis [24] make a different design choice: when the in-memory buffer reaches capacity, instead of flushing the entire in-memory index, they choose to flush only a portion of the term space (a contiguous range of terms based on lexicographic sort order), performing a merge with the corresponding on-disk portions of the inverted lists. The advantage of this is that it does not lead to a proliferation of index segments, compared to Lester et al. [19].

The above review focuses on incremental indexing, but of course, there has been a lot of work on indexing in general; see [38] for a survey. One way to ensure contiguous postings lists is to adopt a two-pass approach [12, 35, 14], which is impractical for incremental indexing. Moffat and Bell [25] proposed a single-pass, sort-based approach (later improved by Heinz and Zobel [15]), in their method, whenever memory is exhausted, the in-memory postings are flushed to disk as separate index segments. A final post-processing step merges these individual segments into a single index. Again, this approach is unsuitable for incremental indexing.

In terms of work specifically focused on in-memory indexing, Luk and Lam [22] proposed an in-memory storage allocation scheme based on variable-size linked lists. However, it is unclear if the approach is scalable: they only report experiments on old TREC collections that are over an order of magnitude smaller than the ones we explore here. Furthermore, their work used a relatively inefficient technique for postings compression (variable-length integers) and does not build full positional indexes, as we do.

Recently, Busch et al. [6] detailed the architecture of Earlybird, the in-memory retrieval engine that powers Twitter’s real-time search. The design takes advantage of the fact that tweets are very short and incorporates a number of optimizations that do not work in the general case—it cannot handle arbitrary collections, as we do. Earlybird adopts a federated architecture, where each server holds a dozen separate index segments, only one of which (the “active” segment) ingests new tweets. In the active segment, postings are not compressed, which simplifies the indexing algorithm. In contrast, we build a single monolithic index and compress postings on the fly, representing a different point in the design space of possible in-memory architectures.

3. APPROACH

3.1 Basic Incremental Indexing Algorithm

Our indexer consists of three main components, depicted in Figure 1: the dictionary, buffer maps, and the segment pool. The basic indexing approach is to accumulate postings in the buffer maps in an uncompressed form until the buffer fills up, and then to “flush” the contents to the segment pool, where the final compressed postings lists reside. Note that in this approach the inverted lists are discontinuous; we return to address this issue in Section 3.2.

The dictionary is implemented as a hash table with a bitwise hash function [28] and the move-to-front technique [34], mapping terms (strings) to integers term ids (see [37] for a study that compares this to other approaches). There is nothing noteworthy about our dictionary implementation, and we claim no novelty in this design. The dictionary additionally holds the document frequency (df) for each term, as well as a head and tail pointer into the segment pool (more details below). In our implementation, term ids are assigned sequentially as we encounter new terms.

A buffer map is a one-to-one mapping from term ids to arrays of integers (the buffers). Since term ids increase monotonically, a buffer map can be implemented as an array of pointers, where each index position corresponds to a term id, and the pointer points to the associated buffer. The array of pointers is dynamically expanded to accommodate more terms as needed. To construct a positional index, we build three buffer maps: the document id (docid) map, the term frequency (tf) map, and the term positions map. As the names suggest, the docid map accumulates the document ids of arriving documents, the tf map holds term frequencies, and the term positions map holds term positions. There is a one-to-one correspondence between entries in the docid map and entries in the tf map (for each term that occurs in a document, there is exactly one term frequency), but a one-to-many correspondence between entries in the docid map and entries in the term positions map (there are as many term positions in each document as the term frequency).

In the indexing loop, the algorithm receives an input document, parses it to gather all term frequencies and term positions (relative to the current document, starting from one) for all unique terms, and then iterates over these unique terms, inserting the relevant information into each buffer map. Whenever we encounter a new term, the algorithm initializes an empty buffer in each buffer map for the corresponding term id. Initially, the buffer size is set to the block size $b$ that will eventually be used to compressed the data (leaving aside an optimization we introduce below to control the vocabulary size). Following best practice today, we use PForDelta [40, 36] with the recommended block size of $b = 128$. The term positions map expands one block at a time when it fills up to accommodate more positions. When the docid buffer for a term fills up, we “flush” all buffers associated with the term, compressing the docids, term frequencies, and term positions into what we call an inverted list segment, described below:

Each inverted list segment begins with a run of docids, gap-compressed using PForDelta; call this $D$. By design, the docids occupy exactly one PForDelta block. Next, we compress the term frequencies using PFor; call this $F$. Note that term frequencies cannot be gap-compressed, so they are left unmodified. Finally, we process the term positions, which are also gap-encoded, relative to the first term position in each document. For example, if in $d_1$ the term was found at positions [1, 5, 9] and in $d_2$ the term was found at positions [3, 16], we would code [1, 4, 4, 3, 13]. The term positions can be unambiguously reconstructed from the term frequencies, which provide offsets into the array of term positions. Since
the term positions array is likely longer than \( b \), the compression block size, the term positions occupy multiple blocks. Call the blocks of term positions \( P_1 \ldots P_m \).

Finally, all the data are packed together in a contiguous block of memory as follows:

\[
[|D|, D, |F|, F, \{P_i, P_i\}_{0 \leq i < m}]
\]

where the \([ \cdot ]\) operator returns the length of its argument. Since all the data are tightly packed in an otherwise unlimited array, we need to explicitly store the lengths of each block to properly decode the data during retrieval.

Each inverted list segment is written at the end of the segment pool, which is where the compressed inverted index ultimately resides. Conceptually, the segment pool is a bounded array with a pointer that keeps track of the current “end”, but in practice the pool is allocated in large blocks and dynamically expanded as necessary. In order to traverse a term’s postings during query evaluation, we need to “link” together the discontiguous segments. The first time we write a segment for a term id, we add its address (byte offset in the segment pool) to the dictionary, which serves as the “head” pointer (the entry point to postings traversal). In addition, we prepend to each segment the address (byte offset position in the segment pool) of the next segment in the chain. This means that every time we insert a new segment for a term, we have to go back and correct the “next pointer” for the last segment. We leave the next pointer blank for a newly-inserted segment to mark the end of the postings list for a term; this location is stored in the “tail pointer” in the dictionary. Once the indexer has processed all documents, the remaining contents of the buffer maps are flushed to the segment pool in the same manner. By default, we build full positional indexes, but our implementation has an option to disable the term position buffers if desired. In this case, the inverted list segments will be smaller, but other aspects of the algorithm remain exactly the same.

Conceptually speaking, the postings list for each term is a linked list of inverted list segments, where each of the segments is laid out in discontiguous monotonically-increasing byte offset positions in the segment pool and linked together with addressing pointers. Segments corresponding to different terms are arbitrarily interleaved in the segment pool. What are the implications of this design? On the positive side, all data in the segment pool are “tightly packed” for maximum efficiency in memory utilization: there are no empty regions and there is no need for special delimiters. During indexing we guarantee that there is no heap fragmentation, which may be a possibility if we simply used \texttt{malloc} to allocate space for each inverted list segment. On the negative side, postings traversal becomes an exercise in pointer chasing across the heap, without any predictable access patterns that will aid in processor pre-fetching across segment boundaries. Thus, as a query evaluation algorithm consumes postings, it is likely to encounter a cache miss whenever it reaches the end of a segment, since it has to follow a pointer. On the other hand, it is not entirely clear if this cache miss is a major concern: since PFiorDelta is block-based, postings are decompressed in blocks even if the inverted lists are contiguously stored in memory.

In addition to “flushing to memory” (i.e., the segment pool) as opposed to flushing to disk, the operation of our indexer is fundamentally different from previous designs. In previous approaches, the in-memory buffer is completely flushed when the capacity limit is reached, which means that inverted lists associated with all terms are written to disk. In contrast, we only flush data associated with the term id whose buffer has reach capacity.

One final optimization detail: we control the size of the term space by discarding terms that occur fewer than ten times (an adjustable document frequency threshold). This is accomplished as follows: instead of creating a buffer of length \( b \) when we first encounter a new term, we first allocate a small buffer equal to the \( df \) threshold. We buffer postings for new terms until the threshold is reached, after which we know that the term will make it into the final dictionary, and so we reallocate a buffer of length \( b \). This two-step process reduces memory usage substantially since there are many rare terms in web collections.
3.2 Segment Contiguity

It is clear that our baseline indexing algorithm generates discontiguous inverted lists. In order to create contiguous inverted lists, we would need an algorithm to rearrange the segments once they are written to the segment pool. Following the “remerging” idea in disk-based incremental indexing, we might merge multiple discontiguous segments belonging to the same term id and transfer them to another region in memory, repeating if necessary. Alternatively, when writing an inverted segment to the segment pool, we might leave some empty space—but since no pre-allocation policy can be prescient, we will either leave too much empty space (wasting memory) or not leave enough (necessitating further copying). These basic designs have been explored in the context of on-disk incremental indexing (see Section 2.2), but we argue that the issues become more complex in memory because we do not have an intermediate abstraction of the file—the indexing algorithm must explicitly manage memory addresses. This amounts to implementing malloc and free for inverted list segments, which is a non-trivial task.

Before going down this path, however, we first examined the extent to which contiguous segments would improve retrieval efficiency, from better reference locality, pre-fetch cues provided to the processor, etc. Let us assume we have an oracle that tells us exactly how long each inverted list is going to be, so that we can lay out the segments end-to-end, without any wasted memory. We simulate this oracle condition by building the inverted index as normal, and then performing in-memory post-processing to lay out all the inverted list contiguously. Obviously, in a real incremental indexing scenario, this is not a workable option, but this simple experiment allows us to measure the ideal performance from the perspective of query evaluation. Thus, we can establish two retrieval efficiency bounds—the query evaluation time on arbitrarily discontiguous inverted lists (the baseline algorithm) and on contiguous inverted lists (the upper bound on query evaluation speed).

Using these two efficiency bounds as guides, we developed a simple yet effective approach to achieving increasingly better approximations of contiguous postings lists. Instead of moving compressed segments around after they have been added to the segment pool, we change the memory allocation policy for the buffer maps. In the limit, if we increased buffer map sizes so that they are large enough to hold the entire document collection in uncompressed form, it is easy to see how we could build contiguous inverted list segments. As it turns out, we do not need to go to such extremes.

In our strategy, whenever the docid buffer for a term becomes full (and thus compressed and flushed to the segment pool), we expand that term’s docid and tf buffers by a factor of two (still allowing the term positions buffer to grow as long as necessary). This means that after the first segment of a term is flushed, new docid and tf buffers of length \(2b\) replace the old ones; after the second flush, the buffer size increases to \(4b\), and then \(8b\), and so on. When a buffer of size \(2^nb\) becomes full, the buffer is broken down to \(2^m\) segments, each segment is compressed as described earlier, and all \(2^n\) segments are written at the end of the segment pool contiguously. This strategy allows long postings to become increasingly contiguous, without wasting space to pre-allocate large buffers to hold terms that turn out to be rare.

To prevent buffers from growing indefinitely and to control the memory pressure, we set a cap on the length of docid and tf buffers. That is, if the cap is set to \(2^nb\), then when the buffer size for a term reaches that limit, it is no longer expanded. This means that the maximum number of contiguous segments allowed in the segment pool is \(2^m\). We experimentally show that for relatively small values of \(m\), around 6 or 7, we achieve query evaluation speeds that are statistically indistinguishable from having an index with fully-contiguous inverted lists (i.e., the oracle condition). The tradeoff of this approach is that we require more transient working memory during the indexing process, and that impacts the size of the collection that we can index. However, we experimentally show that the additional memory requirements for implementing this approach are reasonable. Note that for on-disk incremental indexing algorithms, the strategy of increasing the in-memory buffer size is generally not considered since those algorithms operate under an assumption of limited memory. In our case, we are simply changing the allocation between transient working memory for performing document inversion and the final index structures. In Section 9 we consider alternative designs and discuss why we settled on this approach.

4. EXPERIMENTAL SETUP

We performed experiments on two standard collections: Gov2 and ClueWeb09. The Gov2 collection is a crawl of .gov sites from early 2004, containing about 25 million pages, totaling 81GB compressed. ClueWeb09 is a best-first web crawl from early 2009. Our experiments used only the first English segment, which has 50 million documents (247GB compressed). For evaluation purposes, we used two sets of queries: the TREC 2005 terabyte track “efficiency” queries, which consist of 50,000 queries total; and a set of 100,000 queries sampled randomly from the AOL query log.

Our indexer, called Zambezi, is implemented in C; it is currently single-threaded. To support the reproducibility of experiments described in this paper, the system is released under an open source license. Since this paper is focused on indexing, we wished to separate document parsing from the actual indexing. Therefore, we assumed that input test collections are already parsed, stemmed, with stopwords removed before indexing. Our reports of indexing speed do not include document pre-processing time.

Experiments were performed on a server running Red Hat Linux, with dual Intel Xeon “Westmere” quad-core processors (E5620 2.4GHz) and 128GB RAM. This particular architecture has a 64KB L1 cache per core, split between data and instructions; a 256KB L2 cache per core; and a 12MB L3 cache shared by all cores of a single processor.

We examined three aspects of performance: memory usage, indexing speed, and query evaluation latency. The first two are straightforward, but we elaborate on the third. For each indexer configuration, we measured query evaluation speed in terms of query latency for two retrieval strategies: conjunctive retrieval using the SviS algorithm, demonstrated by Culpepper and Moffat [8] to be the best approach to postings intersection, and disjunctive query processing using the Wand algorithm [4], which represents a strong baseline for top \(k\) retrieval (with BM25). Note that for both cases we first indexed the collection, and then performed query evaluation at the end—the interleaving of indexing and retrieval.
operations is beyond the scope of this work, since it involves tackling a host of concurrency challenges.

The SvS algorithm sorts postings lists in increasing order of length. It begins by intersecting the two smallest lists. At each step, the algorithm intersects the current intersection set with the next postings list, until all lists are consumed. Each intersection is carried out using a one-sided binary search, or “galloping” search. Note that with SvS we compute the entire intersection set.

The WAND algorithm uses a pivot-based pointer-movement strategy which enables the algorithm to skip over postings of documents that cannot possibly be in the top \( k \) results by reasoning about the maximum score contribution for each term. Recently, Ding and Suel [14] introduced an additional optimization called Block-Max WAND (BMW) that increases query evaluation speed. The idea is that instead of using the global maximum score of each term to compute the pivots, the algorithm uses a piece-wise upper-bound approximation of the scores. However, this algorithm is not directly applicable for incremental indexing: in order to compute a score upper-bound for each block, the index needs accurate global statistics (such as average document length in the case of BM25). Thus, there are only two options: either use statistics at the time the block is written, which might compromise correctness, or continually update the upper bounds whenever the statistics change, which is slow.

Since our focus is not on query evaluation, we believe that experiments with SvS and WAND are sufficient to illustrate the tradeoffs our indexing algorithm manifests. Note that we do not consider any learning to rank approach [20] because it represents an orthogonal issue. In a modern multi-stage web search architecture [21,22], an initial retrieval stage (e.g., using SvS or WAND) generates documents that are then reranked by a machine-learned ranking model.

Finally, we compared our Zambezi indexer against two open-source retrieval engines: Zettai [19] (v0.9.3), which implements the geometric partitioning approach of Lester et al. [19] and Indri [10] (v5.1). To ensure a fair comparison with the other systems, we disabled their document parsing phase and used the already parsed documents as input. As with our algorithms, reports of indexing speed do not include time spent on document pre-processing.

5. RESULTS

5.1 Query Latency

Table 1 summarizes query latency for conjunctive query processing (postings intersection with SvS). The average latency per query is reported in milliseconds across five trials along with 95% confidence intervals. Each column shows different indexing conditions: 1b is the baseline algorithm pre-

| Query | 1b | 2b | 4b | 8b | 16b | 32b | 64b | 128b | Contiguous |
|-------|----|----|----|----|-----|-----|-----|------|------------|
| Gov2  |    |    |    |    |     |     |     |      |            |
| Terabyte | 14.4 (±0.2) | 14.2 (±0.1) | 13.9 (±0.1) | 13.6 (±0.1) | 13.3 (±0.1) | 13.2 (±0.1) | 13.1 (±0.1) | 13.1 (±0.1) |
| AOL   | 20.2 (±0.4) | 19.7 (±0.1) | 19.3 (±0.2) | 19.0 (±0.3) | 18.8 (±0.3) | 18.7 (±0.5) | 18.4 (±0.2) | 18.3 (±0.1) | 18.2 (±0.2) |
| ClueWeb09 | 49.7 (±0.2) | 47.1 (±0.1) | 45.9 (±0.4) | 44.4 (±0.5) | 42.9 (±0.4) | 42.0 (±0.3) | 41.6 (±0.1) | 41.6 (±0.4) | 41.3 (±0.1) |
| AOL   | 87.5 (±1.6) | 83.2 (±0.5) | 80.7 (±0.3) | 75.5 (±0.5) | 75.7 (±0.8) | 75.8 (±0.3) | 75.2 (±0.2) | 75.0 (±0.6) | 75.3 (±1.2) |

Table 1: Average query latency (in milliseconds) for postings intersection using SvS with different buffer length settings. Results are averaged across 5 trials, reported with 95% confidence intervals.

As with the conjunctive query processing case, we analyzed query latency by length. The results, however, were not particularly insightful: as expected, query latency increases with length, and the performance differences between the three conditions were so small that the plots essentially overlapped. For this reason, we did not include the corresponding figures here.

5.2 Query Latency

Table 2 summarizes query latency for disjunctive query processing (postings intersection with SvS). Each of \([2, 4, 8, \ldots, 128]b\) represents a different upper bound in the buffer map growing strategy described in Section 3.2. The final column marked “contiguous” denotes the oracle condition in which all postings are contiguous; this represents the ideal performance.

From these results, we see that, as expected, contiguous postings lists (1b) yield slower query evaluation: on Gov2, queries are approximately 10% slower, while for ClueWeb09, the performance dropoff ranges from 16% to 20%. For higher values of \( b \), we allow the buffer maps to increase in length: at 32b, query evaluation performance is statistically indistinguishable from the performance upper bound (i.e., confidence intervals overlap). That is, we only need to arrange inverted list segments in relatively small groups of 32 to achieve ideal performance. Later, we quantify the memory requirements of allocating larger buffer maps.

Figure 2 illustrates query latency by query length, for the AOL query set on Gov2 and ClueWeb09, using different conditions. Not surprisingly, the latency gap between contiguous and the 1b condition widens for longer queries. On the other hand, the difference between a contiguous index and the 32b condition is indistinguishable across all query lengths—the lines practically overlap in the figures.

Table 2: Average query latency (in milliseconds) to retrieve the top 1000 hits in terms of BM25 using WAND (5 trials, with 95% confidence intervals).

For conjunctive query processing, we used the WAND algorithm to retrieve the top 1000 documents using BM25. Table 2 summarizes these experiments on different collections and queries. For space considerations, we only report results for select buffer length configurations. These results are consistent with the conjunctive processing case. A maximum buffer size of 32b yields query latencies that are statistically indistinguishable from a contiguous index. Note that the performance difference between fully-contiguous postings lists and 1b is statistically indistinguishable across all query lengths—the lines practically overlap in the figures.

For disjunctive query processing, we used the WAND algorithm to retrieve the top 1000 documents using BM25. Table 2 summarizes these experiments on different collections and queries. For space considerations, we only report results for select buffer length configurations. These results are consistent with the conjunctive processing case. A maximum buffer size of 32b yields query latencies that are statistically indistinguishable from a contiguous index. Note that the performance difference between fully-contiguous postings lists and 1b is statistically indistinguishable across all query lengths—the lines practically overlap in the figures.
Figure 2: Query latency using SvS for the AOL query set, by query length for different buffer length settings.

Figure 3: Indexing speed for Indri and Zettair with different memory limits, and Zambezi (our indexer) with different contiguity conditions on Gov2 and ClueWeb09. Error bars show 95% confidence intervals across 3 trials.

5.2 Indexing Speed

Figure 3 shows indexing times for our indexer, Zettair, and Indri. For Zettair and Indri, we varied the amount of memory provided to the system. Note that we were not able to provide Zettair with more than 4GB memory due to its implementation. In C, the maximum size of an individual array is $2^{32}$ and circumventing this restriction would have required substantial refactoring of the code, which we did not undertake. For our indexer, we report results with the different postings list contiguity conditions. Error bars show 95% confidence intervals across 3 trials. In all conditions we do not include document pre-processing time.

Indexing time with Indri appears to be relatively insensitive to the amount of memory provided, but it is overall slower than both Zettair and our indexer. However, the performance differences are more pronounced for Gov2 than for ClueWeb09. With Zettair, the maximum size of the memory buffer does have a significant impact on indexing time. Ironically, giving Zettair more memory actually slows down indexing speed! We explain this counter-intuitive result as follows: smaller in-memory segments are more cache-friendly; for example, our system has a 12MB L3 cache, so in the 20MB condition, more than half of the segment will reside in cache. On the other hand, smaller segments require more merging. In general, it seems like the first factor is more important: for ClueWeb09, indexing is fastest with 20MB buffers. For Gov2, increased cache performance is not sufficient to compensate for additional time spent merging, but the optimal balance occurs with 128MB buffers, which is still relatively small.

These results show that our in-memory indexing algorithm is not substantially faster (and for some conditions on Gov2, actually slower) than an on-disk algorithm. Why might this be so? First, on-disk indexing algorithms have been studied for decades, and so it is no surprise that state-of-the-art techniques are well-tuned to the characteristics of disks. Second, cache locality effects and memory latencies slow down in-memory algorithms as the memory footprint increases—this is confirmed by the Zettair results, where, in general, giving the indexer more memory reduces performance. How does this happen? A larger in-memory footprint means that we are accumulating more documents in the buffer, and hence managing a larger vocabulary space. This causes more “cache churn”, since whenever we encounter a rare term, its associated data (e.g., recently-inserted postings) are fetched into cache, displacing another term’s. Since the rare term is unlikely to appear in another document soon, it is wasting valuable space in the cache. In contrast, the merging operations for the on-disk algorithms access data in a very predictable pattern, thus creating opportunities for the pre-fetchers to mask memory latencies. To test this hypothesis, we ran Indri with a memory size of 120GB on Gov2, and the indexer took 38k seconds to complete, which is roughly double the times reported in Figure 3. This result appears to support our analysis.

\[*Lester (p.c.) concurs with our explanation.*\]
Finally, we note that end-to-end system comparisons conflate several components of indexers that may have nothing to do with the algorithms being studied—for example, we use PForDelta compression, whereas Zettair does not. The research question in our study, the impact of postings lists contiguity, is primarily addressed with experiments that consider different contiguity configurations. However, Zettair and Indri results provide external points of reference to contextualize our findings.

5.3 Memory Usage

All inverted indexing algorithms require transient working memory to hold intermediate data structures. For on-disk incremental indexing algorithms, previous work has assumed that this working memory is relatively small. In our case, there is no hard limit on the amount of space we can devote to working memory, but space allocated for holding intermediate data takes away from space that can be used to store the final compressed postings lists, which limits the size of the collection that we can index for a fixed server configuration.

At minimum, our buffer maps must hold the most recent \( b \) docids, term frequencies, and associated term positions (leaving aside the rare terms optimization in Section 3.1). In our case, we set \( b = 128 \) to match best practices PForDelta block size; any smaller value would compromise decompression performance. In order to increase the contiguity of the inverted list segments, we increase the length of the buffers, as described in Section 3.2. This of course increases the space requirements of the buffer maps.

Figure 4 shows the maximum size of the buffer maps for different contiguity configurations, broken down by space devoted to docids, term frequencies, and term positions. The reported values were computed analytically from the necessary term statistics, making the assumption that all terms reach their maximum buffer size at the same time, which makes these upper bounds on memory usage. To facilitate comparison across the two collections, we normalized the values to the \( b \) condition; in absolute terms, the total buffer map sizes are 12.6GB for Gov2 and 22.1GB for ClueWeb09. It is no surprise that as the maximum buffer length increases, the total memory requirement grows as well. At 128d, where we allow the buffer to grow to 128 blocks of 32-bit integers, the algorithm requires 71% more space for Gov2 and 95% more space for ClueWeb09 (compared to the \( b \) configuration). At 32b, which from our previous results achieves query evaluation performance that is statistically indistinguishable from contiguous postings lists, we require 44% and 70% more memory for Gov2 and ClueWeb09, respectively.

As reference, the total size of the segment pool (i.e., size of the final index) is 31GB for Gov2 and 62GB for ClueWeb09. This means, on the Gov2 collection, setting the maximum buffer length to 1b, 32b and 128b results in a buffer map that is approximately 41%, 59%, and 69% of the overall size of the segment pool, respectively. Similarly, for ClueWeb09, the buffer map sizes are approximately 32%, 54%, and 63% of the size of the segment pool, respectively. These statistics quantify the overhead of our in-memory indexing algorithms.

Note that most of the working memory is taken up by term positions; in comparison, the requirements for buffering docids and term positions are relatively modest. In all cases the present implementation uses 32-bit integers, even for term positions. We could easily cut the memory requirements for those in half by switching to 16-bit integers, although this would require us to either discard or arbitrarily truncate long documents. Ultimately, we decided not to sacrifice the ability to index long documents.

The total number of unique terms is 31M in Gov2 and 79M in ClueWeb09. Since these collections consist of web pages, most of the terms are unique and correspond to JavaScript fragments that our parser inadvertently included and other HTML idiosyncrasies; such issues are prevalent in web search and HTML cleanup is beyond the scope of this paper. Our indexer discards terms that occur fewer than 10 times, which results in a vocabulary size of 2.9M for Gov2 and 6.9M for ClueWeb09. Of these, Figure 5 shows the percentage of terms that require a maximum buffer length of \( m \times b \), for different values of \( m \) in our contiguity settings. For example, the 1b bar represents terms whose document frequencies are \( \geq 10 \) but \( < 128 \). The 2b bar represents terms whose document frequencies are \( \geq 128 \) but less than \( 1b + 2b = 384 \), and so on. The 128b bar represents terms whose document frequencies exceed the maximum buffer length of 128 blocks.

From this we can see why significantly increasing the \( b \) value only yields a modest increase in memory requirements.

Finally, the average size of each inverted list segment for terms with a buffer length of 1b is about 300 bytes; for terms that require a buffer of length of 2b, the average length is around 600 bytes. For terms with a buffer of length \( > 2b \), this value is about 800 bytes. These statistics make sense...
since 1b terms may have less than a document frequency of 128, and in general, rarer terms have smaller term frequencies, and hence fewer term positions.

6. DISCUSSION

Let us summarize our findings so far: compared to “ideal” contiguous postings lists, a linked list of inverted list segments yields slower query evaluation. However, if the algorithm creates groups of 32 inverted list segments by buffering, we can achieve performance that is statistically indistinguishable from ideal performance. Thus, postings list contiguity is important but only up to a point.

From the processor architecture perspective, there are two interacting phenomena that contribute to this result: First, the memory latencies associated with pointer chasing in the linked lists are masked by PForDelta decompression. With contiguous postings lists, predictable striding allows prefetching to hide memory latencies, but postings are traversed in “bursts” since after reading each segment the algorithm must decode the blocks. Thus, decompression can hide cache misses in the case of discontiguous postings: while the processor is decompressing one segment, it can dispatch memory requests for the next (since the instructions are independent). Second, query evaluation is more complex than a simple linear scan of postings lists: SvS performs galloping search for intersection and WAND uses pivoting to skip around in the postings lists. This behavior creates unpredictability in memory access patterns and reduces opportunities for the pre-fetchers to detect striding patterns. To illustrate this, consider the difference between ideal performance and the 1b baseline condition: the performance gap is much smaller for WAND than for SvS. This makes sense, since at each stage, SvS is intersecting the current postings list with the working set; this implies greater cache locality, so we obtain a bigger performance boost with contiguous postings list. On the other hand, WAND pivots from term to term and at each step may advance the current pointer by an unpredictable amount; thus, even if the postings lists are contiguous, the processor may encounter cache misses. Thus, it makes less of a difference if the postings lists are discontiguous to begin with.

The tradeoff in our approach is that our algorithm needs to devote working memory to buffering the relevant data, which takes away from space that can be devoted to the final compressed index—this limits the size of the collection that we can handle. In practice, however, we do not believe this is an issue. In our experiments, 128GB of memory is more than enough to handle 50 million documents (ClueWeb09). Most production systems adopt a partitioned architecture, where the entire document collection is split into smaller parts and assigned to individual servers. The size of each partition is governed by many factors, one of which is query evaluation speed. In order to maintain constant query evaluation speed, the growth of the partition size is limited by processor speed and memory latencies. However, the maximum possible partition size is dictated by the amount of memory available. Based on current trends, memory capacities are growing much faster than the speed of individual processor cores and improvements in memory latencies. Thus, the overhead required by our incremental indexing algorithm will become less and less of a concern over time. Even still, there are relatively simple optimizations that we can implement to significantly reduce the working memory requirements. Currently, all values in our buffer maps are 32-bit integers, but that is overkill for most cases. Buffered values can be stored in compressed form using standard techniques such as variable-sized integers or Rice codes. This will especially reduce the space requirements for storing term positions, whose values are generally small and can be gap-compressed on the fly.

As an alternative to increasing the size of the buffer maps to increase postings list contiguity, we could pre-allocate memory in the same manner as on-disk incremental algorithms (i.e., when flushing an inverted list segment to the segment pool, leave extra space). We had considered this approach, but rejected it for a number of reasons. First, reserved space in our setting would need to be in multiples of the average inverted list segment due to the block nature of PForDelta compression, so neither the constant nor proportional strategy of Tomasic et al. [32] will work. However, since inverted list segments do not have fixed sizes, there is greater potential for waste: say, we only reserved 800 bytes, but the next inverted list segment occupies 801 bytes. Second, since no pre-allocation policy can be prescient, there will inevitably be fragmentation in the segment pool unless we start moving data around to eliminate memory gaps—at which point, we’re basically writing a garbage collector (another non-trivial challenge). In contrast, our buffering approach does not create any empty space in the segment pool, and the additional memory requirements of the buffer maps are transient (i.e., freed after the indexing process is complete). For these reasons, we feel that our approach is superior and rejected the alternative.

7. CONCLUSION AND FUTURE WORK

One area of future work is to explore the interleaving of indexing and retrieval operations, which requires care to manage concurrent access to global data structures. Since this paper focuses on indexing and not on query evaluation per se, we have set aside this complexity for now. However, we see at least two methodological issues that need to be addressed in such a study: first, we do not have a realistic model of document and query arrival, and second, we need new metrics to quantify query evaluation speed to factor out differences due to queries issued at different times over indexes of different sizes.

In this paper, we have taken an initial foray into studying in-memory indexing algorithms, an underexplored region in the design space. Our finding that postings list contiguity matters only to a certain extent contributes to our understanding of information retrieval algorithms in the context of modern processor architectures. We believe that other aspects of information retrieval algorithms will also need to be reexamined, because the tradeoffs become very different once disk is removed from the picture.

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