Index Maintenance for Time-Travel Text Search

Avishek Anand[†], Srikanta Bedathur[‡], Klaus Berberich[†], Ralf Schenkel[*]

[†]Max-Planck Institute for Informatics
Saarbrücken, Germany

[‡]IIIT-Delhi
New Delhi, India

[*]Saarland University
Saarbrücken, Germany

{aanand,kberberi}@mpi-inf.mpg.de, bedathur@iiitd.ac.in,
schenkel@mmci.uni-saarland.de

ABSTRACT

Time-travel text search enriches standard text search by temporal predicates, so that users of web archives can easily retrieve document versions that are considered relevant to a given keyword query and existed during a given time interval. Different index structures have been proposed to efficiently support time-travel text search. None of them, however, can easily be updated as the Web evolves and new document versions are added to the web archive.

In this work, we describe a novel index structure that efficiently supports time-travel text search and can be maintained incrementally as new document versions are added to the web archive. Our solution uses a sharded index organization, bounds the number of spuriously read index entries per shard, and can be maintained using small in-memory buffers and append-only operations. We present experiments on two large-scale real-world datasets demonstrating that maintaining our novel index structure is an order of magnitude more efficient than periodically rebuilding one of the existing index structures, while query-processing performance is not adversely affected.

Categories and Subject Descriptors

H.3.3 [**Information Search & Retrieval**]: Search process

General Terms

Experimentation, Algorithms, Performance

Keywords

Time-Travel Text Search, Index Maintenance, Web Archives

1. INTRODUCTION

In recent years, there has been an increasing awareness that born-digital contents, such as those on the Web, are ephemeral but often worth preserving. Organizations involved in the preservation of web contents include non-profits (e.g., the Internet Archive [1] and the Internet Memory Foundation [2]), for-profit companies, as well as national libraries and universities. The motivations behind such web archives are diverse and range from preservation of cultural heritage to compliance with legal requirements.

Web archives typically contain multiple versions of every document that reflect the evolution of its content over time. Interfaces provided to users in order to access archived contents, though, are still limited, for instance, to URL-based lookup & browsing as in the Internet Archive's Wayback Machine or simple keyword search. Motivated by this, *time-travel text search* has been proposed as an extension of standard text search by temporal predicates. Users can thus combine a keyword query (e.g., financial crisis) with a time interval (e.g., `[2006, 2008]`) to retrieve all document versions from the archive that are considered relevant to the given keywords and existed during the given time interval. Different index structures [3, 4, 7] have been proposed to efficiently support time-travel text search, incurring controllable overhead either in terms of index size or response time when compared to standard text search.

However, none of the existing index structures for time-travel text search can easily be updated when additional document versions are archived. To keep up with the state of the web archive, they thus have to be rebuilt periodically. While this used to be the case as well for standard inverted indexes, their maintenance in the presence of *insertions*, *modifications*, and *deletions* of documents is now fairly well-understood [11, 19, 24].

Our approach put forward in this work efficiently supports time-travel text search and handles additions of new document versions to the archive. It distinguishes between *active versions*, as the most recent and still current document versions, and *archive versions*, as the document versions already superseded by a more recent version of the same document. To search the active versions, a standard incrementally updatable inverted index [11, 18] is employed, which we will not discuss further. Our focus instead is on searching the archive versions. We propose a novel index structure to this end, building on our own sharded index for time-travel text search [4], and describe how it can be maintained incrementally when document versions are superseded and thus need to be migrated from the active index.

The original sharded index for time-travel text search relies on a method to horizontally partition each index list, so that any time-travel query can be processed without sequentially reading index entries that do not overlap with the query time-interval. It then relaxes the horizontal partitions determined (the so-called *shards*), taking into account the I/O characteristics of the storage infrastructure, encoded as a parameter η reflecting the cost ratio between random seeks and sequential reads. The method guarantees for every *relaxed shard* that the *expected number* of wastefully read index entries is bounded by η. We are more stringent in this work and consider the worst case by bounding the *maximum number* of wastefully read index entries instead. This allows us to develop an online incremental sharding algorithm that keeps only a small in-memory buffer for every shard in the archive index. We show that our online algorithm is within an approximation factor of $(2 - \frac{2}{\eta+2})$ and hence results in at most two times the optimal number of relaxed shards.

We conducted experiments on the revision history of the English Wikipedia and the UKGOV web archive, as two large-scale real-world datasets. Our results show that incrementally maintaining our novel index structure is an order of magnitude more efficient than periodically rebuilding a sharded index for time-travel text search. Query processing performance, in addition, is not adversely affected and even improves in some cases. We therefore believe that the proposed approach provides the best of both worlds – update ability and efficient query processing – two key features needed when searching web archives but missing so far.

The rest of this paper unfolds as follows: Section 2 introduces our model and notation. Section 3 recaps key ideas behind the sharded index that we build upon. Section 4 describes our incremental sharding method to maintain the index. Section 5 presents the overall architecture of our system. Our experimental evaluation is the subject of Section 6. Finally, we relate to existing research in Section 7 and conclude in Section 8.

2. DATA AND QUERY MODEL

We consider a collection $\mathcal{D}$ of versioned documents that change over time. Each document d is uniquely identified by an identifier id_d. At time t, document d may have an active version d^* and zero or more archive versions $\langle d^1, d^2, \ldots \rangle$. Each (active or archive) version d^i of d comes with a valid-time interval $I(d^i) = [\, begin(d^i),\, end(d^i)\,)$ that denotes when that version was the active version of d; for d^*, $end(d^*) = \infty$ and $t \in I(d^*)$. We furthermore assume that all the $I(d^i)$ are disjoint.

The active version of a document turns into an archive version when the document is re-crawled and either a new active version is found or the document was removed from the Web. In both cases, the end time of the old version is set to the current time.

We consider time-travel queries over $\mathcal{D}$ that consist of a set of terms $Q = \{q_1, \ldots, q_m\}$ and a time interval $[b_Q,\, e_Q]$. When evaluated, this query retrieves the set of document versions that satisfy the keyword query Q and existed at any time during the time interval $[b_Q,\, e_Q]$.

3. INDEX ORGANIZATION

We now describe our index organization and briefly recap the sharded index for time -travel text search [4] that we build upon in this work.

Our system distinguishes between *active versions*, as those that are the most recent and still current version of a document, and *archive versions*, as those that have already been superseded by a more recent version of the same document. To search them, our system employs separate indexes, coined *active index* and *archive index*.

Both our indexes are based on the established inverted index [28] that associates each term with an *index list*. Each entry in the index list, $\langle id_d, I(d^i), s \rangle$, consists of a document identifier id_d, a valid-time interval, $I(d^i) = [begin(d^i), end(d^i)]$, and a payload s. The specifics of the payload depend on the retrieval model and the types of queries to be supported – it can be empty, a scalar value (e.g., capturing term frequency), or include positional information. When no confusion arises, we simply use $begin(p)$ and $end(p)$ of an index entry p to refer to the valid-time interval boundaries of the corresponding document version.

Queries that only ask for current information contained in active versions can be processed using only the active index, which corresponds to the live index that search engines maintain on the current Web. Time-travel queries that also ask for information from the past contained in archive versions are processed using both the active index and the archive index in combination.

The active index is implemented as an incrementally updatable inverted index [11, 18]. Depending on the fraction of time-travel queries among all queries posed to the system, index lists in the active index can be organized to efficiently support queries on active versions or time-travel queries. For the former, index entries may be ordered by their document identifier to allow for more efficient query processing, possibly together with additional structures [8, 12, 21, 26]. For the latter, index entries may be ordered by the begin boundary of their valid-time interval to support efficient filtering of too recent document versions.

The archive index is implemented as a sharded index [4], whose key ideas we now briefly recap. The sharded index distributes entries in an index list over disjoint partitions coined *shards*. Entries within a shard are ordered by the begin boundary of their valid-time interval. In addition, each shard comes with an *impact list* that maintains, for every possible begin boundary b_Q of a query time-interval, the position of the earliest entry in the shard whose valid-time interval contains the begin boundary b_Q. In practice, impact lists can be represented compactly and kept in main memory, as described in [4].

When processing a time-travel query, all shards for the query terms in Q are read from the position stored in their impact list for the begin boundary b_Q of the query time-interval, as opposed to, from their beginning. Per shard this involves one random seek to get to the indicated position followed by a number of sequential reads. One can safely stop reading a shard once the first index entry with a begin boundary larger than e_Q has been seen. The query processing cost thus depends on the number of shards, each of which is accessed with a random seek, and the total number of index entries that are read sequentially. Every method that assigns index entries to shards has to consider these two factors.

We now describe how index entries can be assigned to shards so as to optimize query processing cost. Since the assignment of index entries to shards solely depends on their valid-time intervals, we describe it as an interval-to-shard assignment problem and use the notions index entry and interval interchangeably. Let us first introduce some basic notation for intervals that we need in what follows. An interval I_j is associated with a begin time $begin(I_j)$ and an end time $end(I_j)$. We say that an interval I_1 subsumes an interval I_2 (for short: $I_1 \sqsupset I_2$), if:

$$begin(I_2) > begin(I_1) \ \wedge \ end(I_2) < end(I_1) \ .$$

An index entry is said to be a wasted read, if it is accessed during query processing although its valid-time interval does not overlap with the query time-interval. Such a wasted read may be caused when an interval I_1 *subsumes* another interval I_2 in the same shard. Assuming that a shard contains only these two intervals, the impact list entry for a begin boundary b_Q of the query time-interval after the end of I_2 will point to I_1 which is stored before I_2, and I_2 will be read even though it does not qualify as query result.

Since all shards for a term are accessed for any time-travel query including the term, the cost incurred due to random seeks is proportional to the number of shards per term. The cost for random seeks and sequential reads can be traded-off with two extremes. On one hand we can eliminate the cost for all but one random seek by having only a single shard per term. On the other hand, we can eliminate wasted reads altogether by creating idealized shards. *Idealized sharding* avoids subsumption entirely, i.e., there are no two intervals I_1 and I_2 with $I_1 \sqsupset I_2$ in a shard. The minimal number of idealized shards for a given set of intervals can be determined using a greedy algorithm, as described in [4].

The best performing solution is usually in between these two extremes, taking into account the I/O characteristics of the storage infrastructure housing the index. *Cost-aware sharding* developed in [4] systematically allows for interval subsumptions, while minimizing the overall number of shards. It thus trades some additional wasted sequential reads for a reduced number of random seeks. The method minimizes the number of shards per index list (and hence the number of random seeks) by systematically merging idealized shards. It thereby ensures that the expected number of wasted sequential reads per shard is below a threshold η encoding the cost ratio between random seeks and sequential reads.

4. INCREMENTAL SHARDING

Incremental sharding takes into account the relative costs of random and sequential accesses by a more restrictive bound on the number of subsumptions for a given shard. It bounds the absolute number of subsumptions for a given shards. This is opposed to cost-aware sharding in [4] where the number of subsumptions per shard were on an average limited to a system-wide parameter. A bound on the number of subsumptions per shard translates to bounding the number of sequential wasted reads. We term this restriction as the *bounded subsumption* property. A shard is said to exhibit a bounded subsumption property if an interval in that shard does not subsume more than η intervals, where η is a system-wide constant same as before. Formally,

DEFINITION 1 (BOUNDED SUBSUMPTION). *A shard S is said to satisfy the bounded subsumption property of limit η if each interval $I_i \in S$ does not subsume more than η intervals:*

$$\forall I_i \in S : |\{ I_j \in S \mid I_j \neq I_i \ \wedge \ I_i \sqsupset I_j \}| \le \eta \ .$$

The problem of minimizing the number of random accesses with a limited number of wasted sequential accesses can be redefined in terms of minimizing the overall number of shards such that each shard exhibits the bounded subsumption. Thus, the problem definition becomes:

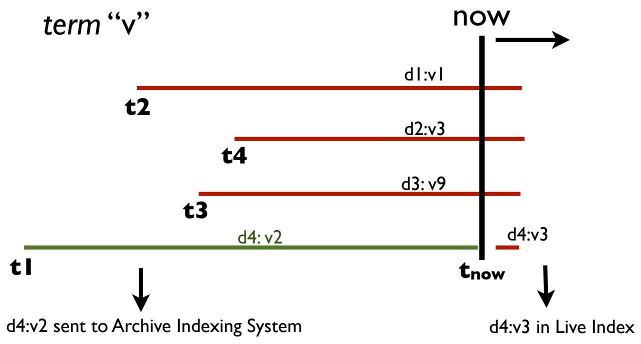


Figure 1: End time order of finalizing versions

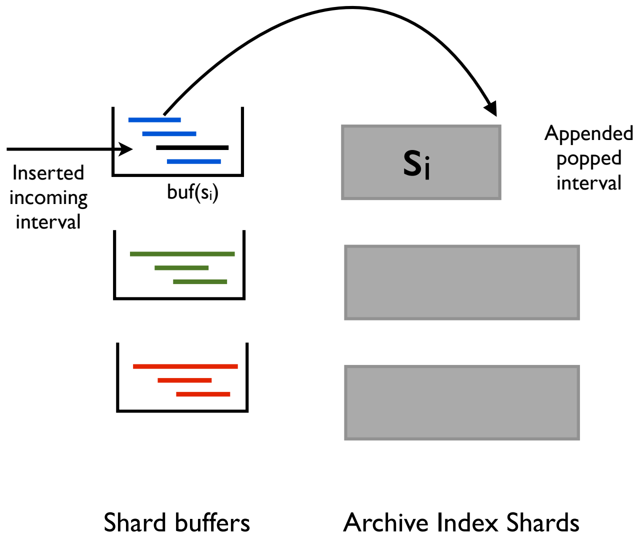


Figure 2: Incremental sharding

DEFINITION 2. *Given a set of intervals $\mathcal{I}$, partition $\mathcal{I}$ into a* minimal set *of shards $\mathcal{S} = \{S_1, \ldots, S_m\}$, $\forall I_k \in S_i,\ I_k \in \mathcal{I}$ where:*

$$S_i \cap S_j = \emptyset \qquad \forall S_i, S_j \in \mathcal{S},\ i \neq j$$
$$\bigcup_i S_i = \mathcal{I}$$

s.t. $\forall S_i \in \mathcal{S}$: S_i satisfies bounded subsumption.

Before attempting to solve the above problem let us discuss certain properties in an archive indexing setting. Firstly, the archive setting is very specific in terms of arrival of the input sequence, i.e., in the order of arrival of new versions to the archive index. Whenever the end time of an existing version is determined, it is sent to the archive indexing system (refer Figure 1). Since versions are generated in the end time order, the input intervals also follow the same order.

Secondly, we do not deal with deletions of versions since a deletion of a document results in an entry in the archive index for that document, and existing versions are never removed. This means that the index steadily grows over time with the older collection indexed by the archive index being a subset of the current collection.

Finally, from the indexing point of view it is preferable to have an updating scheme which appends newly created postings at the end of the index list. The major benefit of an append operation is that the indexes built for the older indexes can be used as partial solutions to build an up-to-date archive index efficiently thus avoiding recomputation. Recomputation of shards with a non-append based technique (say cost-aware sharding) is expensive because it involves processing the entire input (existing data along with the new updates) thus limiting its applicability to an update aware indexing system.

Another benefit with an append operation is the avoidance of the expensive decompression and compression cycles in building the new updated index. While merging two index lists by employing recomputation the corresponding shards of each term are completely decompressed to form usable input for the sharding algorithm. After recomputing the new set of shards are compressed back again for storage. The most popular compression algorithms used in index list compression are based on gap-encoding schemes which are local schemes and hence append friendly. Hence, rather than optimally solving the problem we look for an approach which is based on an append only operation to the existing shards and exploits the end time order of input arrival. In the following subsection we introduce the *incremental sharding* algorithm which apart from being incremental also has an approximation guarantee.

4.1 Incremental Sharding Algorithm

We present the *incremental sharding algorithm* which is an update aware incremental algorithm with a factor $(2 - \frac{2}{\eta+2})$ approximation algorithm(cf. Algorithm 1). Apart from having the natural benefit of being an append only algorithm it also exploits the end time arrival order of the intervals by processing the intervals in that order thus avoiding expensive sort operations on the input.

The algorithm processes intervals in the end time order (cf. line 1) and creates or updates shards incrementally. It follows a scheme of immediate assignment but deferred append of an interval to a shard. For each shard we maintain a *shard buffer* of size $\eta + 1$ and an *shard begin time*. The assignment of the interval to a shard is based on the begin time of the shard and the shard buffer defers the actual writing or appending of the interval of the shard to satisfy the bounded subsumption property. In other words the shard buffer maintains the interval until it deems it right to be appended to the end of the shard.

When an interval, $I[i]$, is processed it is either assigned to an existing shard based on the interval and shard begin times (cf. line 15) or it results in the creation of a new shard (lines 7-10). The creation of a new shard involves setting the begin time of the shard to zero and placing the chosen interval in its shard buffer. Until the buffer reaches its capacity of η the begin time of the shard remains zero. The shard begin time is first updated only when the an interval is popped out of it after the buffer reaches its capacity $\eta + 1$. When the assignment for the interval is decided, say S_t, it is placed in the respective shard buffer $buf(S_t)$ (cf. line 19). The incremental sharding chooses the shard whose begin time has the least difference with the begin time of the incoming interval (cf. line 15).

The shard buffers determine the relative position of the intervals in the shard where it will be finally stored. The insertions into the buffer are made to preserve the begin time order (cf. line 19) which in turn ensures a begin time order when intervals are removed from it. This is diagramatically shown in Figure 2. Only the first interval or the interval with the minimum begin time is removed from the buffer to limit the buffer size to $\eta + 1$ (line 23) and it is appended to the end of its corresponding shard S_t. The shard buffers also ensure that no interval in a shard subsumes more than η intervals. This is done by setting the begin time of a shard $S_t.begin$ to the first interval $begin(first(buf(S_t)))$(or the interval with the least begin time) of the shard buffer as in line 24. The interval with the minimum begin time in the shard can subsume the maximum number of intervals and any interval with a begin time lesser than it is dissallowed.

Note the use $\cup$ in lines 23 and 30 to indicate the *append* operation on the shard that is logically organized as a list of intervals in their begin time order.

Algorithm 1 Incremental Sharding Algorithm

```
1: Input: (i)$\eta$, (ii)$\mathcal{I}$ sorted in increasing order of end times
2: $\mathcal{S} = \emptyset$    // incremental sharding
3:
4: for $i = 1 .. |\mathcal{I}|$ do
5:     //creates new shard
6:     if $\neg\exists S \in \mathcal{S} : S.begin \le begin(I[i])$ then
7:         create new shard $S_{new}$ and $buf(S_{new})$
8:         $S_{new}.begin = 0$
9:         add $I[i]$ to $buf(S_{new})$
10:        $S = \mathcal{S} \cup \{S_{new}\}$
11:    end if
12:
13:    //find the best candidate shard for assignment
14:    $S_{cand} = \{S_i \mid S_i \in \mathcal{S} \wedge S_i.begin \le begin(I[i])\}$
15:    $S_t = \underset{g \in S_{cand}}{argmin}\ (begin(I[i]) - g.begin)$
16:
17:    //update buffers and begin times of shards
18:    if $S_t \neq S_{new}$ then
19:        insert $I[i]$ into $buf(S_t)$ in begin time order
20:    end if
21:    if $|buf(S_t)| = \eta + 1$ then
22:        //first element in the buffer finalized
23:        $S_t = S_t \cup removefirst(buf(S_t))$
24:        $S_t.begin = begin(first(buf(S_t)))$
25:    end if
26: end for
27:
28: //finally append the buffer intervals to the shards
29: for $S \in \mathcal{S}$ do
30:     $S = S \cup buf(S)$
31: end for
32:
33: Output: $\mathcal{S}$ is the incremental sharding.
```

4.2 Approximation Guarantee

THEOREM 1. *Incremental sharding is a $(2 - \frac{2}{\eta+2})$ approximation.*

We approach the proof by first proving two lemmas. Assuming that incremental sharding produces m shards, we construct a worst case scenario. For notational convenience let us assume that shards are numbered according to their creation times in incremental sharding, i.e., S_1 was created before S_2 and so on.

Lemma 1 (Descending Begin Times). *If incremental sharding created a shard S_{i+1} after S_i, then $S_i.begin > S_{i+1}.begin$.*

Proof. We prove this property by induction over increasing number of intervals $I_i \in \mathcal{I}$ which are added in in end time order, i.e, $end(I_{i+1}) > end(I_i)$.

$i = 1$: For the first interval I_1 the property holds since there are no earlier shards.

$i \rightarrow i+1$: Let there be n existing shards $\mathcal{S} = \{S_1 \cdots S_n\}$. Depending on the begin time of the $(i+1)$th interval $begin(I_{i+1})$ we consider the following two cases:

Case 1: If $begin(I_{i+1}) < S_k.begin$, $1 \leq k \leq n$, then I_{i+1} forms a new shard S_{new} and the begin of the shard $S_{new}.begin$ is less than all the existing shard begin times. This proves the claim.

Case 2: Assuming $\exists S_k : begin(I_{i+1}) \geq S_k.begin$ and on addition of I_{i+1} to S_k there is a violation of the descending begin time order of shards, i.e. , $S_k.begin > S_{k-1}.begin$. This means that $S_{k-1}.begin < begin(I_{i+1})$ and I_{i+1} should have been assigned to S_{k-1} due to a smaller difference according to the induction hypothesis of $S_{k+1}.begin > S_k.begin$, $\forall 1 \leq k < n$. ☐

Lemma 2 (Incremental subsumption). *An interval added to S_i subsumes at least $(i-1)(\eta+1)$ intervals.*

Proof. Note that $S_i.begin$ refers to the time of the first interval in the buffer of shard S_i or the earliest begin time in the shard buffer $buf(S)$. By Lemma 1 we know that there is an ordering of the shard begin times. Hence for an interval I assigned to S_i the following holds – $begin(I) < S_{i-1}.begin < \cdots < S_1.begin$. Since we assume end time arrival order of intervals it subsumes all intervals in $i-1$ shards buffers, which are $S_1, ..., S_{i-1}$. Further the fixed buffer size of $\eta+1$ results in making the subsumptions lower bounded by $(i-1)(\eta+1)$. ☐

We recollect the *Staircase Property* of a shard as introduced in [4] as a property which requires the intervals to be in their begin time order and additionally disallowing subsumptions among any pair of intervals in the shard. We further need to introduce the notion of *stalagtite sets* and *stalagtite groups*. A *stalagtite set* Λ_s is a set of time intervals such that,

$$\forall p, q \in \Lambda_s, begin(p) \leq begin(q) \Rightarrow end(p) > end(q).$$

Stalagtite groups (cf. Figure 3) are a collection of sets of intervals such that choosing one interval from each of these sets results in a *stalagtite set*.

Lemma 3 (Stalagtite grouping). *Stalagtite grouping with a staircase property in each shard is the worst case for incremental sharding.*

Proof. From the previous lemma, any input resulting in m shards from incremental sharding will have at least intervals with $\eta+1$, $2(\eta+1)$, $\cdots$, $(m-1)(\eta+1)$ subsumptions in $S_2, S_3, \cdots, S_m$ respectively. Let us suppose that the set of subsumed intervals when the first interval added to S_i be represented as $sub(S_i)$. To reduce the overall number of shards we should strive for a configuration with minimum number of subsumptions. This is possible when $sub(S_1) \subseteq sub(S_2) \subseteq \cdots \subseteq sub(S_m)$ and $|S_i| = \eta+1, \forall i = 1, \ldots, m$. This arrangement forms a *stalagtite group*(cf. Figure 3) with each of the groups having a cardinality of $\eta+1$.

Additionally, each of these stalagtite groups should have a staircase arrangement to allow for the maximum capacity - η - out of place insertions. Any additional interval or misaligned interval either increases subsumption or reduces capacity for out of place insertions. Any removal of intervals on the other hand result in contradiction to the original assumption that there are m shards from incremental sharding. ☐

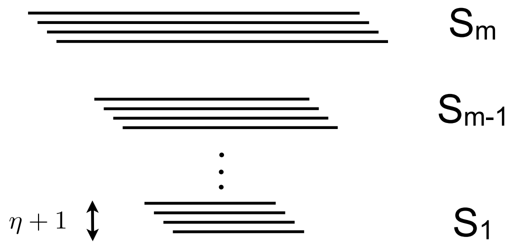


Figure 3: Stalagtite groups

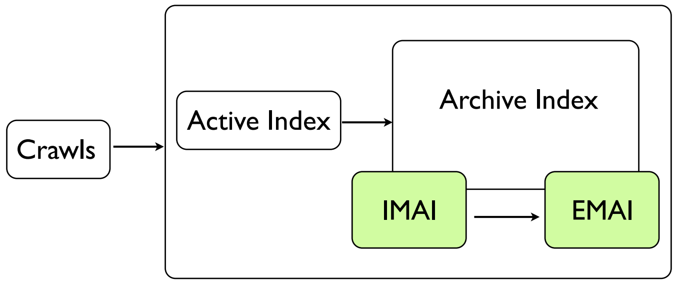


Figure 4: System architecture

Now we can complete the proof for Theorem 1.

Proof. From the Lemma 3 we know that there are m stalagtite groups with each group residing in the shards formed from incremental sharding. It is easy to see that none of the optimal shards will have more than $2\eta+1$ intervals. Thus we choose an assignment where we try to minimize minimum number of shards, i.e., choose as many shards with $2\eta+1$ intervals as possible. One such assignment is when we assign η of the $\eta+1$ intervals of S_i to S_{m+1-i}, $\forall i \leq \frac{m}{2}$. The remaining $\frac{m}{2}$ intervals (an interval from each S_i) can then be placed in $\frac{m}{2(\eta+1)}$ shards. Hence for m shards created by incremental sharding we get a minimum of $\frac{m}{2} + \frac{m}{2(\eta+1)}$ shards. Notice that we can have other arrangements which give the same number of minimum shards. The ratio

$$\frac{|S|}{OPT} = \frac{m}{\frac{m}{2} + \frac{m}{2(\eta+1)}} = 2\left(1 - \frac{1}{\eta+2}\right)$$

proves that incremental sharding is a factor $(2 - \frac{2}{\eta+2})$ approximation algorithm. ☐

5. SYSTEM ARCHITECTURE

Figure 4 shows a high-level overview of the architecture of a search engine using our incremental sharding method. It consists of

- The *active index* for all active versions of documents, consisting of an in-memory inverted list for each term that keeps the active versions of documents containing this.
- The *archive index* for all archive versions of documents, consisting of an inverted list for each term that is

organized in shards. The archive index consists of an in-memory index *IMAI* and an on-disk index *EMAI*, both organized in shards.

- A *crawler* that continuously crawls the target Web sites, for example a predefined set of domains or the complete Web.

When the crawler encounters a new document that has been unknown so far, it adds it to the active index; this is an inexpensive operation since the active index is in main memory. When a document is found again, it is checked for changes (using, for example, a fingerprinting technique such as [9, 16]). If changes are detected, the active version of that document turns into an archive version (with end time equal to the crawl time) and is sent to the archive index, and index entries for the new active version are added to the active index.

The archived version is then added to the in-memory archive index by first creating the corresponding postings for each term, which are then added to the in-memory archive index using the incremental technique from Section 4. Figure 1 shows an example for this, where in a crawl at time t_{now} a new version v_3 for document $d4$ is detected. This results in firstly adding a new version $d4 : v3$ with a begin time t_{now} to the affected terms in the active index. Secondly, the end time of $v2$ is finalized and the posting $\langle d4 : v2, [t_1, t_{now}], \mathit{score} \rangle$ with the complete interval information is send to the archive indexing system. In the archive indexing system this posting is processed by placing it in the shard buffer of term "v" and updating the IMAI from the popped posting in the buffer as shown in Figure 2. As soon as the in-memory index IMAI is full, entries are merged into the disk-based archive index EMAI, merging corresponding shards; this essentially corresponds to incremental maintenance of standard inverted lists.

6. EXPERIMENTAL EVALUATION

All our algorithms were implemented in Java 1.6, within the time-travel indexing system presented earlier in [4]. Experiments were conducted on Dell PowerEdge M610 servers, with 48 GB of main memory, and attached to a large disk array through iSCSI.

The two data collections used in our experiments are: (i) the English Wikipedia revision history, referred to as the **WIKI** collection, which contains the edit history from January 2001 until December 2005 excluding all the minor edits, and (ii) a web archive, referred to as the **UKGOV** collection, provided by the Internet Memory Foundation (previously European Archive), consisting of weekly crawls of 11 government websites within U.K. during 2004 and 2005. The characteristics of these two collections are briefly summarized in Table 1. For the ease of experimentation, we rounded the time-stamps of versions to the nearest day for all datasets.

6.1 Index Management

We build indexes based on incremental sharding (INC) and cost-aware sharding as in [4] (CA) algorithms with relaxation parameter(η) values 10, 100 and 1000. All sharded indexes are stored on disk in flat files containing both the lexicon (i.e., pointers to the shards for each term) as well as sharded term lists. At run time, the lexicon is read completely into memory, and for a given query the appropriate shards are retrieved from disk. For compression we employ 7-bit + gap encoding [20].

We simulate the index updates needed for our incremental index maintenance as follows: we first created partial indexes for each month containing postings of only those versions that have end time within that month. The index is incremented, starting from an empty index, by merging partial index of each month in sequence. We employed *immediate-merging* [10] to create one consolidated index at the end of every monthly merge operation, and each sharded posting list in the index is incrementally maintained using our INC algorithm. We compared this with CA sharding, which recomputes the entire sharding for the combined index every time from scratch. In other words, all shards of a posting list in the currently merged index are read and decompressed, the corresponding list from the partial index for the next month is also read and decompressed, these two are combined, and finally, a new sharding is generated using the CA algorithm for the merged index which is written in compressed form to disk.

6.2 Query Workloads and Execution

We compiled one query workload for each dataset, by extracting frequent queries from the AOL query logs that were temporarily available during 2006. For querying the WIKI dataset, we extracted the 300 most frequent queries which had a result click on the domain `en.wikipedia.org`; similarly for UKGOV, we compiled 50 queries which had result hit on `.gov.uk` domains. Using these keyword queries, we generated a time-travel query workload with 5 instances each for the following three different temporal predicate granularities: *week*, *month* and *year*.

For query processing we employed conjunctive query semantics i.e., query results contain documents that include all the query terms. We use wall-clock times (in milliseconds) to measure the query processing performance. The runtimes were measured on warm caches using only a single core. Specifically, each query was executed five times in succession and the average of the last four runs was taken for a more stable and accurate measurement of the query runtime.

6.3 Results

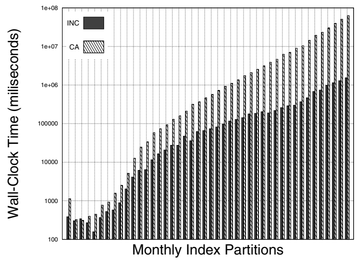
Index Maintenance Performance

Figures 5 and 6 show results of our experiments on index maintenance with WIKI and UKGOV datasets respectively. Note the log-scale used on the y-axis in these charts, which represents the time-taken for the consolidated sharded index to be built in milliseconds. It is quite evident from these charts that the INC algorithm for maintaining the index is an order of magnitude faster than CA. Note that for UKGOV we report maintenance times for the first seven months only which is already smaller than time taken to merge the entire index for two years using INC. This efficiency comes from two advantages that INC enjoys over CA: first, recomputing the sharding by CA on the merged index takes much of the time and grows as the index size grows. Since INC does not recompute the sharding, its performance improves significantly. Second, it does not have to decompress, merge and shard the entire list before writing do the disk. Instead, it has to just read two posting lists in parallel and append corresponding shards (without decompressing), and write to the disk. From

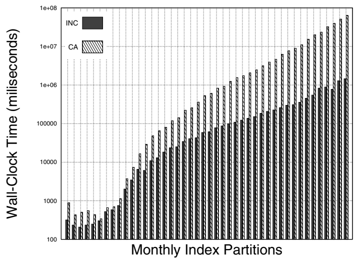
Dataset	Coverage	Size (in GB)	$\mathcal{N}$	$\mathcal{V}$	μ/σ
WIKI	2001 to 2005	~700	1,517,524	15,079,829	9.94 / 46.08
UKGOV	2004 to 2005	~400	685,678	17,297,548	25.23 / 28.38

Datasets with no. of documents $\mathcal{N}$, no. of versions $\mathcal{V}$, average number of versions per documents μ, and standard deviation σ.

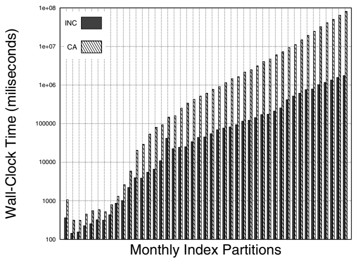
Table 1: Characteristics of datasets used



(a) $\eta = 10$



(b) $\eta = 100$



(c) $\eta = 1000$

Figure 5: Performance of index maintenance - WIKI

our experiments we observe that recomputation of shards accounts for an average of 45% of the entire maintenance time. Compression and decompression take upto 15% of the overall time but since we use 7-bit encoding for compression we expect that a more involved compression technique would only increase the maintenance time. It should be noted that in our simulation we do not perform an append, instead we resort to creating a new index file in each step – incurring additional overheads. Thus, the performance of INC can be further improved by carefully implementing advanced index merging methods.

Effect on Query Processing

To assess the effect of using INC for index maintenance on query processing performance, we used the final index computed for each dataset – i.e., after merging the last partial index at end of 5 years in case of WIKI and after the last partial index at the end of 2 years in case of UKGOV. We compared the performance of answering queries using this index against the query performance over a newly created *archive index* for the entire collection, sharded using CA. Since the active index, as mentioned in 5 is common to both INC and CA, we omitted the query processing time over the active index from our measurements. We considered indexes obtained using three relaxation parameter values $\eta = 10$, 100, 1000. We report runtimes, measured in milliseconds, averaged over queries for three granularities of temporal predicates we considered – *week*, *month* and *year*, as described in Section 6.2. Results are shown in Figures 7 and 8 for WIKI and UKGOV datasets respectively.

As one can observe from these charts, the sharded index generated using INC compares quite favorably with the combined sharded index computed using CA. This behavior is consistent across all the granularities of temporal predicate for all values of η parameter. In some small number of cases, the performance of INC is slightly better than that of CA, and is never worse. Further, we also compared the average number of shards generated by both the algorithms with different values of η. These results are summarized in Table 2. As these results show, using INC in most cases generates fewer number of shards on average for each posting list, reducing the number of random accesses required during query processing. So, when the underlying storage system has high cost of random accesses, then it seems more beneficial to query processing performance to use INC to maintain the index than using CA.

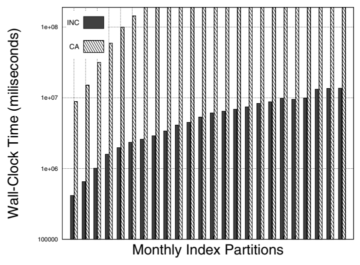
		Sharding	
Dataset	η	INC	CA
WIKI	10	23.37	32.83
	100	13.32	11.41
	1000	5.83	4.42
UKGOV	10	10.93	13.16
	100	6.84	10.35
	1000	4.14	4.79

Table 2: Average number of shards per term

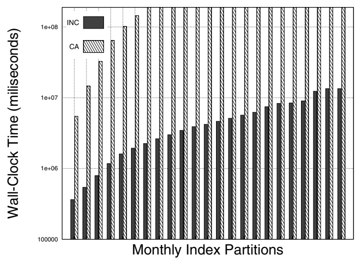
7. RELATED WORK

We now put our work in context with existing research. This can be categorized into (a) work on maintaining inverted indexes when faced with changes in the document collection and (b) approaches that make search aware of temporal information associated with documents. No work, to the best of our knowledge, has been done at the intersection of the two categories.

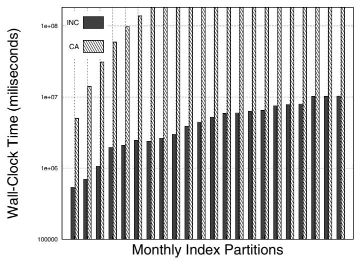
Given that the construction of inverted indexes is well understood and can easily be parallelized, one existing maintenance strategy has been to rebuild the index periodically. Returning stale query results, most of the time, is an obvious disadvantage of this approach. For a long time, though, this has been the approach taken by major search engines on the Web. Only lately, Peng et al. [24] have addressed



(a) $\eta = 10$

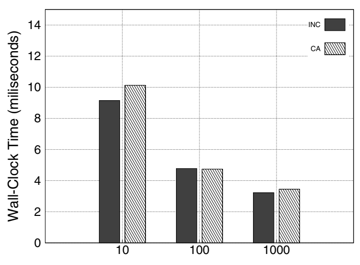


(b) $\eta = 100$

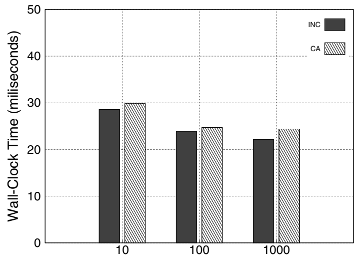


(c) $\eta = 1000$

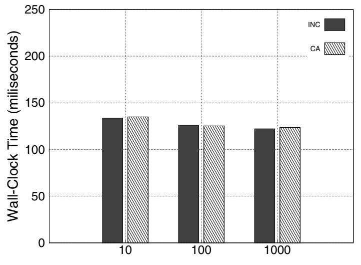
Figure 6: Performance of index maintenance – UKGOV



(a) Week



(b) Month



(c) Year

Figure 7: Query processing performance with varying granularity of temporal predicate – WIKI

the issue of handling updates in web-scale indexes. Instead of rebuilding the index, Lester et al. [19] suggest to collect updates in an in-memory index that is then merged, from time to time to amortize costs, with a disk-resident inverted index. This merge can either be performed in-situ, thus modifying posting lists at their current location, or by storing entirely new posting lists. A hybrid approach that chooses between these alternatives is described by Büttcher et al. [11]. Guarajada and Kumar [13] can be seen as another extension that leverages query logs to determine terms whose posting lists mandate eager maintenance. In a spirit similar to log-structured methods [23], Lester et al. [18] propose to keep multiple indexes of geometrically increasing size and merge them, when they overflow, in a rolling manner. Query results reflecting the current state of the document collection can be obtained in these approaches by executing queries both on in-memory and disk-resident indexes. For more detailed discussions of inverted index maintenance, we refer to the recent textbooks by Büttcher et al. [10] and Manning et al. [20], as well as, the survey by Zobel and Moffat [28].

Constructing indexes for (versioned) document collections with a high degree of redundancy has been an active area of research lately. Anick and Flynn [5], as the earliest approach, applies techniques from version-control systems to a text index. Zhang and Suel [27] propose a two-level index that avoids repeatedly indexing redundant content. Herscovici et al. [17] employ a sequence-alignment formulation to address the same problem. Berberich et al. [7] present the idea of time-travel text search, incorporating temporal predicates into text search, and describe a vertically partitioned (or, sliced) inverted index to support it efficiently. Anand et al. [4], as the work that our methods build upon, show that time-travel text search can be supported equally efficiently by building a horizontally partitioned (or, sharded) inverted index. He et al. [14, 15] have focused on improving compression techniques for inverted indexes on versioned document collections. As a final note, the problem of indexing and querying data with associated temporal information has been studied intensively in the database community – a survey of existing approaches is given by Salzberg and Tsotras [25] present. Becker et al. [6], being based on the B^+-Tree, and Muth et al. [22], as a log-structured method inspired by the LSM-Tree [23], are two database approaches that explicitly deal with updates.

8. CONCLUSIONS

This paper presented incremental sharding, an efficient maintenance technique for indexes in web archives. It uses only cheap append operations to add newly arrived versions to the existing index. It can be smoothly integrated into a search engine for both live and archived documents. Experiments demonstrated that the technique is an order of magnitude more efficient than recomputing the index.

Our future work will focus on an full-fledged implementation of our proposed system. We will further study the influence of different techniques for inverted list maintenance.

Acknowledgments

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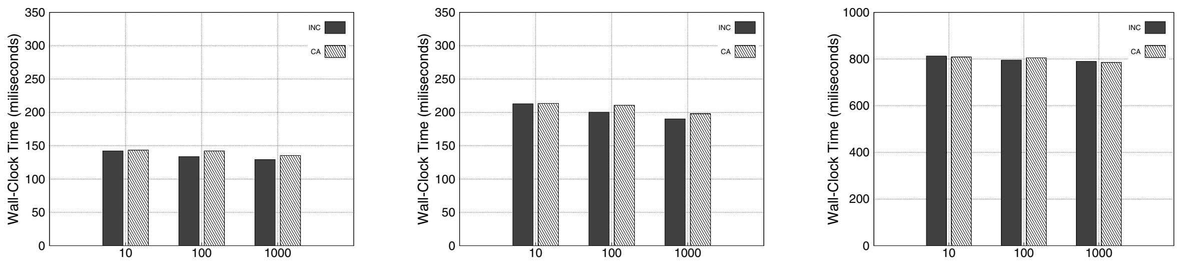

(a) Week (b) Month (c) Year

Figure 8: Query processing performance with varying granularity of temporal predicate – UKGOV

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