

Access Time Tradeoffs in Archive Compression

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Abstract. Web archives, query and proxy logs, and so on, can all be very large and highly repetitive; and are accessed only sporadically and partially, rather than continually and holistically. This type of data is ideal for compression-based archiving, provided that random-access to small fragments of the original data can be achieved without needing to decompress everything. The recent RLZ (relative Lempel Ziv) compression approach uses a semi-static model extracted from the text to be compressed, together with a greedy factorization of the whole text encoded using static integer codes. Here we demonstrate more precisely than before the scenarios in which RLZ excels. We contrast RLZ with alternatives based on block-based adaptive methods, including approaches that “prime” the encoding for each block, and measure a range of implementation options using both hard-disk (HDD) and solid-state disk (SSD) drives. For HDD, the dominant factor affecting access speed is the compression rate achieved, even when this involves larger dictionaries and larger blocks. When the data is on SSD the same effects are present, but not as markedly, and more complex trade-offs apply.

1 Introduction

Large data archives are often retained for long periods. Examples include web crawls; site edit histories for resources such as the Wikipedia; query, proxy, and click logs; and many other forms of meta-data associated with the way we store and access information. Such archives are rarely decoded in full, and even partial-access operations may be infrequent. Moreover, the data might be highly repetitive, with occasional very long repeated strings, and repeated strings that are widely separated. There is thus considerable interest in specialized compression techniques that provide a high level of space saving for such data, plus the ability to support random access to small fragments of it.

The Relative Lempel-Ziv (RLZ) compression approach is designed for archives like these [5]. It involves a plain-text *dictionary* extracted from the collection of documents via fixed-interval sampling across their concatenation. The documents are then factored against the dictionary using the standard Lempel-Ziv greedy parsing approach, and factor descriptions consisting of copy offsets and copy lengths are represented with static integer codes. Because the dictionary and encodings are both static, decoding is possible from any point in the encoded stream, provided only that a corresponding code-aligned byte or bit

address is given for the document that is required. Moreover, decoding is fast – during decoding operations the dictionary is stored in memory uncompressed, allowing rapid access to factors that can then be copied directly to the output stream as required. More details of the RLZ approach are given in Sect. 2.

While the approach provided by RLZ is indeed a good solution to the question of archive compression, other methods based on *adaptive* compression mechanisms are available. For example, standard tools like GZip and xz can be applied on a per-block basis. The block size then becomes an important parameter that trades compression effectiveness against access speed. The larger the block size, the better the compression rate, but the longer it takes for a fragment of text to be reconstructed, since decompression must start at the beginning of a block.

Our purpose in this paper is to provide detailed evidence of RLZ’s capability in archive compression. Our analysis includes the effects of the storage device chosen, and both hard-disk drives (HDD) and solid-state disk (SSD) storage are employed. We analyze the factors that determine the time required to access a fragment of text from an arbitrary location in a large corpus, and show how different compression techniques can be evaluated. The approaches explored include making use of a facility provided by the standard ZLIB library in which a “priming” text enhances compression effectiveness during the start-up phase of GZip’s Lempel-Ziv implementation. The various options are compared on the 426 GiB GOV2 crawl of the .gov domain, which contains a broad mix of HTML, PDF, and other document formats.

Based on those experiments, we conclude that for HDD the dominant factor affecting access speed for random decoding is compression effectiveness, with block size a secondary factor; whereas for SSD decompression speed is also a factor. Our results confirm and extend those of Hoobin et al. [5], providing additional insights into the behavior of this important archiving technique. Our new implementation of RLZ will be made available on completion of the project, so that other compression approaches can also be incorporated as they are developed.

2 RLZ Compression

We now provide a brief description of the RLZ archive compression mechanism [5].

Forming a Dictionary. The collection of documents to be stored are concatenated to make a single large file; we let C denote that single string, and $|C|$ be its length in bytes. Two parameters are then identified: the *dictionary size*, denoted $|D|$ (with D to be used for the dictionary); and the sample size s , chosen to be a factor of $|D|$. The dictionary is formed by taking $|D|/s$ samples, each s bytes long, from C , extracting them at regular $|C|/(|D|/s)$ -byte intervals. For example, if $|C| = 64$ GiB and $s = 1$ kiB, then a dictionary of $|D| = 64$ MiB would be formed by concatenating a total of 65,536 samples, extracted every 1,048,576 bytes of C . Figure 1 shows the process of extracting regular samples from C to form the dictionary D , regardless of the underlying document boundaries.

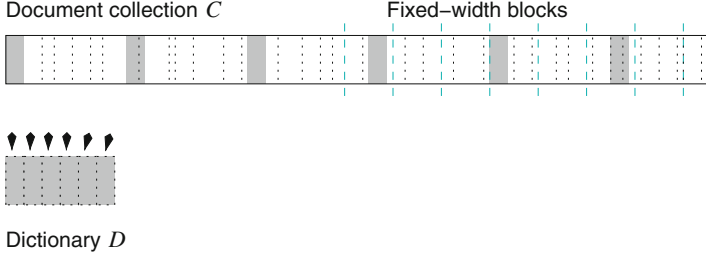


Fig. 1. Constructing the RLZ dictionary D by selecting regular samples from the document collection C . Document boundaries in C are shown by dotted lines; block boundaries (over part of the collection) by dashed lines.

Factoring the Collection. Once D has been formed, C is broken into a sequence of *blocks*, and each block independently *factored* against D , using a left-to-right greedy approach. The blocks might be variable-length and formed by considering individual documents in the collection; might be variable-length and formed by taking groups of documents to reach some minimum size; or might be fixed-length and formed by taking some exact number of bytes. In our implementation we adopt the latter approach, meaning that access to any byte range or to any particular document requires that the corresponding block or blocks be identified and retrieved.

To generate the factorization for each of the blocks, D is indexed via a suffix array or similar structure, so that for an arbitrary string S , the set of longest-matching prefixes of S that appear in D can be identified. Starting at the beginning of each block, factors relative to D are identified and represented by a pair of integer values: the *length* of the factor, and its *offset* in D . If the next character in the block does not appear in D , a *literal* is generated – a factor length of zero, and then an ASCII character code rather than a dictionary offset. There are a range of ways in which the presentation of literals can be optimized, including the application of a minimum match length, or separating them into a distinct third stream. These alternatives are explored in Sect. 4; Hoobin et al. [5] assume that literals are sufficiently rare that intermingling them in the stream of offsets will not adversely affect compression effectiveness. Except when specifically described otherwise, references to factor offsets below include any literals that may have been required. The last factor in each block is truncated so that it finishes at the block boundary. The compressed equivalent of each fixed-length block is then the fundamental access unit for decoding, with higher-level operations such as document retrieval and byte-range retrieval implemented on top of the block access routines.

Compression Rate. The total cost of storing C is the cost of storing D , plus the cost of storing all of the $\langle \text{offset}, \text{length} \rangle$ pairs. The dictionary can be stored using any desired compression mechanism, and is fully decoded into memory prior to subsequent access operations. Even stored uncompressed, it is typically

a small fraction of the original collection. Continuing the previous example, $|D|/|C| = 0.1\%$, and a compressed representation of D should occupy well under 0.03% of $|C|$.

The majority of the space required is in the $\langle offset, length \rangle$ pairs. As already noted, they are separated into two streams on a per-block basis, with each stream coded using a static method such as 32-bit or minimal-width binary integers, or the variable-width byte-oriented `vbyte` approach [9]. The two coded streams are then typically padded to a byte or word boundary, concatenated to make a single unit, and a small prelude added that includes a count of the number of factors contained. Continuing with the same example, suppose that C is partitioned uncompressed into blocks of 16 kiB; that the average factor length is 20 bytes; that each *offset* is coded in $\log_2 |D| = 26$ bits; and that almost all factor lengths are coded in one byte each (`vbyte` codes for factor lengths of up to 127). Then each factor requires 34 bits, and the offsets and lengths for a block are stored in around 3.4 kiB, a compression rate of approximately $3.4/16 \approx 22\%$. Previous experimental results with RLZ suggest that all these various estimates are reasonable [5], and they are further confirmed in the experiments described in Sect. 4.

Random Access Decoding. To provide random-access decoding, index pointers to each block in the compressed integer stream are maintained in an auxiliary structure. The block size determines the number of index points and hence the size of the index, which is important because the index must also be retained in memory during access operations. In the same example, with blocks of 16 kiB, a set of 4,194,304 indexing pointers into the compressed stream is required, with each pointer 34 bits long to address a compressed file of approximately 16 GiB. That is, in the example an index to allow random access to blocks consumes 17 MiB, a further overhead.

To decode a fragment of C specified by an uncompressed byte range (for example, if one document is required, and a mapping from document identifiers to byte addresses is available) standard mod/div arithmetic is performed to determine the ordinal numbers of the block or blocks that are required. The block index (required to be memory resident) is then used to determine the address of the bundle of de-interleaved $\langle offset, length \rangle$ pairs for that block, and a file operation undertaken to fetch the relevant data from secondary storage. The dictionary D (also memory resident) is then used, with $D[offset]$ to $D[offset + length - 1]$ copied to a decode buffer for each $\langle offset, length \rangle$ factor extracted from the compressed blocks. The required range of bytes from within the block can then be written to the output stream once the block decode buffer is filled. That is, after a compressed block has been fetched into main memory, reconstructing a fragment of C consists of decoding two sequences of integers using static integer codes, and then copying strings. Both operations are fast. Further blocks are fetched and decoded if required, until the byte range specified in the query has been delivered.

Ferrada et al. [2] have also considered random access in RLZ mechanisms.

Memory Footprint. Compression effectiveness is in part determined by the amount of space used for the dictionary, as another dimension of effectiveness-efficiency trade-off. For example, if the memory required (64 MiB + 17 MiB in the example scenario) must be reduced for some reason, either the block size can be increased, potentially affecting access speed; or the dictionary size decreased, potentially affecting compression rate. If the block size is increased to 64 kiB, the index reduces to 4.3 MiB. The drawback, of course, is that four times as much data must be transferred into main memory to fulfill a request, and more of it is likely to be required to be decoded as well, unless internal structure is added within each block. As is demonstrated in the experiments below, transfer and decoding times are usually small, and block sizes in the tens of kilobyte range are acceptable. The uncompressed dictionary D is then the dominant memory requirement during random-access decoding. To mitigate this cost, methods have been developed for pruning the dictionary to remove unused or under-used strings [7].

Access Time. In a memory-to-memory context, string-copy decoders similar to RLZ generate text at around 250 MiB–300 MiB per second.¹ A compressed block derived from 64 kiB of C can thus be decoded in around 0.25 ms. But that can only happen once it has been fetched from secondary memory. Table 1 provides indicative performance figures for mechanical (HDD) and solid-state (SSD) secondary memory devices. In a mechanical disk, there is a non-trivial startup time for each data transfer, involving (with high probability) a seek operation to move the read head, followed by a delay resulting from rotational latency. Solid-state disks achieve higher data transfer rates, and commence the data transfer relatively quickly after the request is received.

Table 1. Performance of different storage media. Extracted from product specifications of current devices: Seagate ST3000DM001 (HDD), Intel SSD 750 Series (SSD).

Medium	Random read latency	Sequential transfer rate
Hard disk (HDD)	8.5 ms	150 MiB/s
Solid-state disk (SSD)	0.12 ms	1000 MiB/s

If compressed blocks are stored on HDD, the seek-plus-latency cost of approximately 8.5 ms dominates the cost of transferring the data (around 0.15 ms for the compressed equivalent of a block of, say, 64 kiB of C), and the cost of decoding that block once it is in memory (around 0.25 ms). Based on this arithmetic, and assuming that each query consists of accessing a 16 kiB segment of C , a throughput of around 110 random-access queries per second should be possible. Of that time, decoding activity occupies less than 3%. On the other hand, if the whole collection is decoded sequentially (meaning that seek and latency times are

¹ <https://github.com/Cyan4973/lz4>, accessed 27 July 2015.

amortized to zero), and if compression effectiveness of 30 % or better is achieved (meaning that decoding cost completely subsumes transfer cost) then data can be handed to another process at the measured peak output rate. Continuing the same example, a rate of 300 MiB decoded per second correspond to up to 5,000 64 kiB-blocks, or 20,000 16 kiB-blocks.

If SSD is used, the situation for random access changes markedly. Now the transfer initialization time is around 0.1 ms, meaning that something like 2,900 64 kiB blocks per second can be fetched and decoded, with the decoding taking around 60 % of the total time. Sequential access continues to be dominated by decoding cost, and remains capped at around 20,000 16 kiB-blocks per second. All of these estimated access time and throughput rates are validated empirically in Sect. 4.

3 Block-Based Adaptive Alternatives

We now consider additional options for archive compression.

Standard Compression Libraries. Standard compression tools such as GZip, BZip2, and xz, are *adaptive*, in that they use dynamic models and codes, so as to be versatile across file types. For example, the well-known GZip compressor adopts the same Lempel-Ziv factorization approach as RLZ, starting each compression run with an empty dictionary, and then adding each parsed factor’s text for possible use in subsequent factorizations. If GZip is applied independently to blocks, its “always-start-from-zero” approach puts it at a disadvantage compared to RLZ, because the global RLZ dictionary allows identification of long factors right from the beginning of every block.

On the other hand, adaptive compression techniques build models that are focused on exactly the content being compressed, and hence have an ability to be locally sensitive in a way that RLZ does not. Adaptive methods are also able to exploit encodings for factor offsets and lengths that are adaptive rather than static, further enhancing their ability to provide locally sensitive compression. That is, while RLZ’s use of a global dictionary and static encodings for factor offsets and lengths gives it an advantage on very short blocks, localized adaptive methods may obtain better compression as the block size is increased. Part of our purpose in this investigation is to explore the options provided by these alternatives.

Block Size. A second area for exploration is the effect of block size. The connection between block size and the size of the block index was discussed above. In the case of RLZ, because it typically uses static integer codes, increasing block size has no effect on compression effectiveness. But if large blocks are passed to an adaptive compression utility, average compression effectiveness is likely to improve, because the start up cost of the model is amortized over a longer section of text. This then raises an interesting trade-off – at what block size does an adaptive dictionary provide better compression than a static RLZ-style dictionary of some given size.

For random-access operations using mechanical disk, the added decoding cost due a large block size may not matter. Even with a block size of 512 kiB, decoding of half a block, to reach a given byte address within it, takes around 0.8 ms; transfer of a full block takes approximately 1.1 ms, assuming a 25 % compression rate; and the seek-plus-latency time of around 8.5 ms is unchanged. That is, it should be possible to extract fragments from a block representing 512 kiB of text in around 11 ms, or at an estimated rate of approximately 90 queries per second.

Batch-Mode Operation. If queries are batched and processed “elevator” style, higher query throughput rates can be achieved, because average disk-seek times are likely to be smaller when the access requests are sorted. For example, if 110 random-access queries per second can be supported without batching, and if batches of sufficient size can be accumulated so that the average seek-plus-latency time drops from 8.5 ms to say 4.5 ms then the same hardware configuration should support approximately 200 queries per second. The drawback is that on average the queries will have much greater latencies before being processed – perhaps measured in tens or hundreds of seconds, rather than tens of milliseconds. In applications that fetch small fragments of a large archive, this mode of operation may still be acceptable.

4 Experiments

A New Implementation. To allow precise characterization of the performance of RLZ compression, we have created a new implementation based on fixed-length data blocks, each compressed independently, with a block index maintained in memory so that random-access queries can be supported. The system is written using ≈ 4000 lines of C++11 code with the help of the `sds` library [4]. We use gcc 4.9.2 running on Ubuntu 15.04 in our experiments, with all optimizations enabled.

We have explored five variants, including three RLZ versions:

- RLZ-UV, using unsigned 32-bit integers for factor offsets, and `vbyte` for factor lengths, as described by Hoobin et al. [5];
- RLZ-PV, using packed $\log_2 |D|$ -bit integers for factor offsets, and `vbyte` for factor lengths; and
- RLZ-ZZ, using ZLIB (the basis of the standard GZip compression utility) version 1.2.8 (<http://zlib.net>) to represent each of the streams of 32-bit factor offsets and the stream of 32-bit factor lengths, on a block-by-block basis.

Each of these three methods makes use of a sampled dictionary. We also applied each of ZLIB and LZ4 (<https://github.com/Cyan4973/lz4>) to independent blocks, without use of a dictionary, following preliminary experimentation that included BZip2 and xz. The latter two were slower, and gave less interesting trade-offs between access speed and compression effectiveness. Finally, as a sixth system and a further baseline, we measured the performance of a COPY mechanism that does no compression at all.

Datasets. Our experiments focus on the GOV2 collection, a crawl of the .gov domain undertaken in early 2004, with documents stored in as-crawled order. This collection contains around 25 million documents as a mixture of PDF, HTML, text, and other formats, averaging 18 kiB each, and totaling 426 GiB.² We use both the full collection and a 64 GiB prefix of it.

Query Streams. We explore three modes of retrieval: **FULL**, in which the archive is decoded sequentially; **RANDOM**, in which a set of 10,000 random unaligned locations is accessed and a 16 kiB fragment retrieved from each; and **BATCH**, in which those same 10,000 locations are accessed, but with the queries sorted by address. The “Sequential” mode explored by Hoobin et al. [5] most closely matches our **FULL** mode, in that they measured retrieval of 100,000 consecutive GOV2 documents. Similarly, their “Query Log” mode corresponds broadly to our **RANDOM** mode, but with 100,000 document requests in the query stream, and hence more possibility of caching affecting throughput.

Hoobin et al. [5] also make use of a second URL-sorted GOV2 collection. They obtain notably different query throughput results for the two orderings, particularly with regard to decoding speed, differences that we were unable to reproduce with our implementation. An examination of their code suggests that the differences arise from a mode in their software that because of compiler optimization inadvertently results in no decoded output being generated. As a result, we believe that the “Sequential” retrieval speeds shown in their Table 5 (including decoding rates as high as 80,000 documents per second) should be discounted; and (for other reasons) possibly some of their other speed results too.³ That is, our work here can be seen in part as representing re-measurement of the techniques Hoobin et al. [5] describe.

Dictionary Size and Formation. The effectiveness of the RLZ mechanism is heavily affected by the dictionary size. In their GOV2 experiments Hoobin et al. [5] work with dictionary sizes between 0.5 GiB and 2 GiB. Here we focus on smaller dictionaries, and explore the range from 16 MiB to 256 MiB for the 64 GiB test file, and the range 64 MiB to 1024 MiB for the full GOV2 collection. As described in Sect. 2, we followed the “standard” approach of selecting fixed-interval samples from the collection, presuming it to have been concatenated into a single large file. Other dictionary construction methodologies have been shown to result in small compression effectiveness gains [7]; we also explored a range of other heuristics, but found the simple interval-based sampling approach to be relatively robust. We used samples of length $s = 1024$ throughout, matching (when $|D| = 1$ GiB) some of the experiments carried out by Hoobin et al. [5]. We tested block sizes of 16 kiB, 64 kiB, and 256 kiB. All compression rates include the cost of storing the dictionary, compressed as a character stream using ZLIB, and the cost of the index table for block access, also stored using ZLIB.

² http://ir.dcs.gla.ac.uk/test_collections/gov2-summary.htm, 27 July 2015.

³ Our concerns in this regard have been communicated to the authors of [5].

horizontal axis; and access speed, measured by the number of 16 kiB blocks accessed per second. Each pane contains 36 plotted points: three RLZ variants, each with three different dictionary sizes and three different block sizes (27 data points); plus two blocked adaptive methods using the same three different block sizes (6 data points); plus the COPY method using the three block sizes. Each color corresponds to a dictionary size, and each point shape corresponds to a method. Within each method, the larger the dictionary size and/or the larger the block size, the better the compression. But increased block sizes also correspond to slower decoding. All six panes show the absolute advantage of using virtually any compression method, with the COPY approach the slowest in several cases, and never the fastest. Data compression often pays for itself. Note also that for each method, dictionary, and block size combination the compression rate is the same across all six panes.

The two left panes confirm that sequential decoding is very fast, with the LZ4, RLZ-UV and RLZ-PV approaches having a moderate speed advantage over the other mechanisms, but with all of the compressed approaches delivering 10,000+ documents (each a 16 kiB unit in these experiments) per second, or 160 MiB+/second. There is little measurable difference in performance between HDD and SSD. Unsurprisingly, the larger the dictionary and/or the larger the block size, the better the compression.

The BATCH and RANDOM modes are much slower. In the two middle panes, depicting BATCH access, there is a clear trend on the HDD for better compression to correspond to higher query throughput, with query rates of between 100 documents (unaligned 16 kiB units in this querying mode) and 200 documents per second, and relatively little differentiation between the compression techniques. On the SSD, much faster rates of 800–2,000 documents per second result, with throughput more sensitive to the choice of compression technique. Finally, the right two panes show the further slowdown arising from RANDOM access. On the HDD, query rates are around 100 documents/second; and on the SSD querying throughput is the same as for BATCH retrieval.

The SSD RANDOM and BATCH querying rates are around half those predicted by the model described in Sect. 2. Measurement of the operating characteristics of the SSD used in the experiments indicate that its mean latency is higher than is shown in Table 1, approximately 0.25 ms per access, explaining the difference between predicted and measured querying rates.

Detailed View – Random Access. Figure 3 shows a focused view corresponding to the two right-hand panes in Fig. 2, measured using the full 426 GiB GOV2 collection, and with the COPY method omitted. It considers only the RANDOM queries, using correspondingly larger dictionaries of 64 MiB, 256 MiB, and 1 GiB, and unchanged block sizes of 16 kiB, 64 kiB, and 256 kiB. At the increased scale of these graphs, it is possible to identify a Pareto frontier for each different dictionary size, and quantify the tension between compression and throughput that is controlled by block size.

For random access, the raw speed of LZ4 is less of an advantage, and it is part of the trade-off frontier only when no dictionary can be used, and when

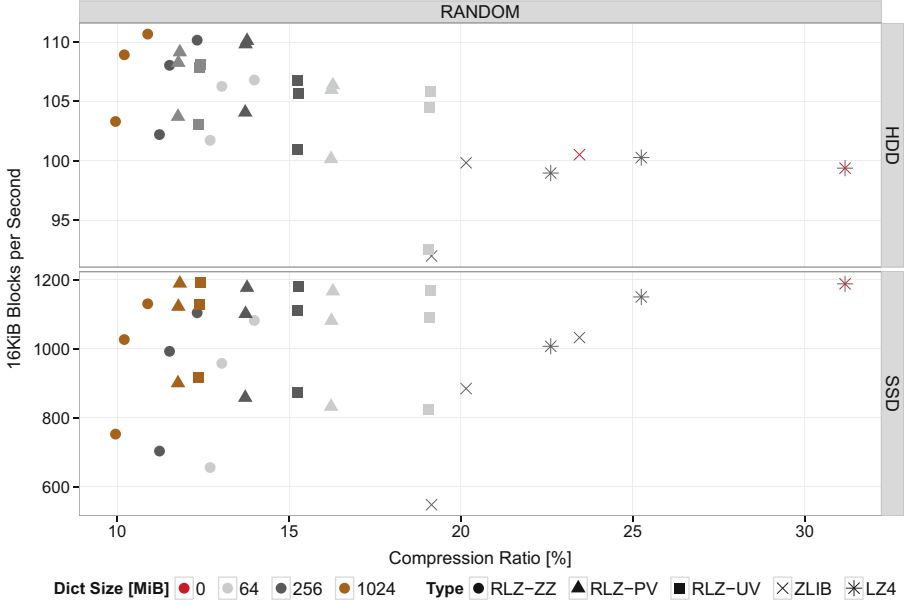


Fig. 3. Query processing rates for the **RANDOM** processing mode, measured as unaligned 16 kiB units retrieved per second, for two types of secondary storage, block sizes of 16 kiB, 64 kiB, and 256 kiB (not individually identified in the plots), and the full GOV2 collection. Note that the upper and lower panes have different vertical scales. (Color figure online)

the fast data rates of SSD are available. If dictionary space is not a restriction, then the RLZ-ZZ methods dominate absolutely for HDD retrieval, and for much of the frontier with SSD retrieval. The remaining part of the SSD frontier is pinned on the RLZ-PV method, highlighting that unaligned bit-wise integers can be processed just as efficiently as can the aligned 32-bit integers preferred by Hoobin et al. [5], and give better compression.

Comparing our results with those of Hoobin et al. [5], we have measured very similar throughput rates for **RANDOM** queries, and by adding blocking to the RLZ-ZZ approach, have slightly improved its compression effectiveness. That small gain, and the reduction in transfer and decoding time that accompanies it, gives the RLZ-ZZ approaches the upper hand, and dictionaries as small as 256 MiB are sufficient to attain high **RANDOM** query throughput even compared to RLZ-PV, and also compact storage. On SSD, the situation is similar, but if query throughput is the primary goal, the RLZ-PV represent the best combination of attributes.

5 RLZ Extensions

We briefly describe two different ways in which RLZ compression can be enhanced.

Table 2. Use of ZLIB priming with the 64 GiB prefix of GOV2. In the ZLIB’ method, a uniform sampled dictionary of 256 MiB is employed. In the RLZ-ZZ’ method, the same 256 MiB dictionary is used, plus two fixed pre-computed integer sequences of 64 kiB containing factor lengths and factor offsets respectively. The two values for each combination are the compression rate, as a percentage of the original collection, and the measured RANDOM-mode throughput, in documents per second using SSD.

Block size	ZLIB		ZLIB’		RLZ-ZZ		RLZ-ZZ’	
	Comp.	Thrpt.	Comp.	Thrpt.	Comp.	Thrpt.	Comp.	Thrpt.
16 kiB	24.83 %	990	22.64 %	955	17.56 %	1043	17.37 %	946
64 kiB	22.29 %	840	21.53 %	825	16.56 %	905	16.47 %	866
256 kiB	21.53 %	513	21.33 %	508	16.26 %	599	16.21 %	581

Priming in RLZ-ZZ. The ZLIB compression library offers the ability to “prime” the compression process, by providing data that is considered to precede the sequence that is to be compressed, thereby providing a model to initialize the dictionary. In the same way that RLZ employs a dictionary, so too can a ZLIB’ approach, in which a uniform sampled dictionary is created, and then each block of data is ZLIB-compressed using priming text drawn from the dictionary in the vicinity of the block being compressed. A similar approach has been demonstrated to be effective when compressing Yahoo email archives [1]. A primed variant of RLZ-ZZ can also be constructed, using pre-computed sequences of factor offsets and factor lengths. Table 2 shows that when the block size is small, priming achieves a worthwhile benefit, but that the gain for larger block sizes is smaller. Priming causes a small decrease in query throughput rates.

Three Streams. Using a full factor – requiring 30+ bits – to represent a literal is expensive, and it is not actually necessary for literals to be mingled with the stream of dictionary offsets. If a third stream is added, containing only the sequence of literals, it can be compressed separately. Once a separate stream is allowed, it also makes sense to force any short factors in to it too – if the next match in the dictionary is of length less than some value *min.literal*, then the entire factor is coded as literals. Similar optimizations are used in many Lempel-Ziv implementations; see, for example, Fiala and Greene [3]. The third stream can be coded using any of the mechanisms already discussed, or any other coding method [6]; here we use of ZLIB for all three.

Table 3 provides a detailed comparison between RLZ-ZZ and RLZ-ZZZ. The gain in compression is larger with a small dictionary than with a large dictionary, since the bigger the dictionary, the less likely it is that short factors will get

Table 3. Use of a three-way split of streams, using $\text{min_literal} = 4$, a 64 GiB prefix of GOV2, and three different dictionary sizes. Values reported are compression rates, as a percentage of the original collection. The final column shows the measured **RANDOM**-mode throughput, as unaligned 16 kiB accesses per second using SSD secondary storage, for the **RLZ-ZZZ** method with a dictionary of 256 MiB, and can be compared with the values in Table 2.

Block size	RLZ-ZZ			RLZ-ZZZ			
	16 MiB	64 MiB	256 MiB	16 MiB	64 MiB	256 MiB	Thrpt.
16 kiB	22.89 %	20.03 %	17.56 %	22.42 %	19.80 %	17.47 %	1029
64 kiB	21.58 %	18.89 %	16.57 %	20.99 %	18.54 %	16.39 %	896
256 kiB	21.18 %	18.54 %	16.27 %	20.57 %	18.17 %	16.06 %	591

generated. That is, the use of three streams can be viewed as being a way of making slightly better use of a small dictionary. Decoding speed is only marginally affected.

6 Summary and Conclusion

We have extended the experimentation of Hoobin et al. [5] to SSD memory, and undertaken a systematic study of blocking effects and access time trade offs in archive compression. The **RLZ-ZZ** static-dictionary method provides an outstanding balance between random access query throughput and compression effectiveness, for both HDD devices and SSD devices. We have also measured the effect of two simple techniques that provide small additional compression gains, without any great loss of throughput.

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