A Grammar Compression Algorithm based on Induced Suffix Sorting

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Abstract

We introduce GCIS, a grammar compression algorithm based on the induced suffix sorting algorithm SAIS, introduced by Nong et al. in 2009. Our solution builds on the factorization performed by SAIS during suffix sorting. We construct a context-free grammar on the input string which can be further reduced into a shorter string by substituting each substring by its correspondent factor. The resulting grammar is encoded by exploring some redundancies, such as common prefixes between suffix rules, which are sorted according to SAIS framework. When compared to well-known compression tools such as Re-Pair and 7-zip, our algorithm is competitive and very effective at handling repetitive string regarding compression ratio, compression and decompression running time.

Introduction

Text compression consists in transforming an input string into another string whose bit sequence representation is smaller. Given the suffix array [1, 2] of a string, one can compute efficiently the Burrows-Wheeler transform (BWT) [3] and the Lempel-Ziv factorization (LZ77) [4–7], which are at the heart of the popular data compression tools 7-zip and GZIP [8].

In 2009, Nong et al. [9] introduced a remarkable algorithm called SAIS, which runs in linear time and is fast in practice to construct the suffix array. Subsequently, SAIS was adapted to compute directly the BWT [10], the Φ-array [7, 11], the LCP array [12], and the suffix array for string collections [13].

In this article we introduce GCIS, a new grammar-based compression algorithm that builds on SAIS. We construct a context-free grammar based on the string factorization performed by SAIS recursively. The rules are encoded according to the

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length of longest common prefixes between consecutive rules, which are sorted lexicographically by SAIS.

Experiments have shown that, regarding repetitive strings, GCIS is competitive with RE-PAIR [14] and 7-zip [15], since GCIS presents the fastest compression time, while maintaining a compression ratio close to RE-PAIR, but being the slower to decode. Hence, it is a practical alternative when considering all trade-off aspects. Moreover GCIS utilizes a novel grammar compression framework in the sense that it is the first, as far as the authors are concerned, based on induced suffix sorting.

Background

Let \( T \) be a string of length \(|T| = n\), \( T = T[1,n] = T[1] \cdot T[2] \ldots \cdot T[n] \), over a fixed ordered alphabet \( \Sigma \). A constant alphabet has size \( \sigma \in O(1) \) and an integer alphabet has size \( \sigma \in n^{O(1)} \). We denote the concatenation of strings or symbols by the dot operator (\( \cdot \)), which can be omitted. We use the symbol \(<\) for the lexicographic order relation between strings.

For convenience, we assume that \( T \) always ends with a special symbol \( T[n] = $ \), which is not present elsewhere in \( T \) and lexicographically precedes every symbol in \( \Sigma \). Let \( T[1,j] \) be the prefix of \( T \) that ends at position \( j \), and \( T[i,n] \) be the suffix of \( T \) that starts at position \( i \) also denoted as \( T_i \) by brevity. We denote the length of the longest common prefix of two strings \( T_1 \) and \( T_2 \) in \( \Sigma^* \) by \( \text{lcp}(T_1, T_2) \).

The suffix array (\( \text{SA} \)) [1, 2] of a string \( T[1,n] \) is an array of integers in the range \([1,n]\) that gives the lexicographic order of all suffixes of \( T \), such that \( T_{\text{SA}[1]} < T_{\text{SA}[2]} < \ldots < T_{\text{SA}[n]} \). The suffixes starting with the same symbol \( c \in \Sigma \) form a \( c \)-bucket in the suffix array. The head and the tail of a bucket refer to the first and the last position of the bucket in \( \text{SA} \).

Let \( G = (\Sigma, \Gamma, P, X_S) \) be a reduced context-free grammar (does not contain unreachable non-terminals). \( \Sigma \) is the terminal alphabet of \( G \); \( \Gamma \) is the set of non-terminals symbols that is disjoint from \( \Sigma \); \( P \subseteq \Gamma \times (\Sigma \cup \Gamma)^* \) is the set of production rules; and \( X_S \in \Gamma \) is the start symbol. A production rule \((X_i, \alpha_i)\) is also denoted by \( X_i \rightarrow \alpha_i \). We say that \( \alpha_i \) is derived from \( X_i \). For strings \( s, t \in (\Sigma \cup \Gamma)^* \), we say that \( t \) derives from \( s \) if it is obtained by application of a production rule in \( P \); we say that \( t \) is generated from \( s \) if \( t \) is obtained by a sequence of derivations from \( s \). We define \(|G|\) as the total length of the strings on the right side of all rules.

Given a string \( T \), grammar compression is to find a grammar \( G \) that generates only \( T \) such that \( G \) can be represented in less space than the original \( T \). Given that \( G \) grammar-compresses \( T \), for \((X_i, \alpha_i) \in P\), we define \( \mathcal{F}(X_i) = s \) as the single string \( s \in \Sigma^* \) that is generated from \( \alpha_i \). The language generated by \( G \) is \( L(G) = \mathcal{F}(X_S) \).

Related work

SAIS [9] builds on the induced suffix sorting technique introduced by previous algorithms [16, 17]. Induced suffix sorting consists in deducing the order of unsorted suffixes from a set of already ordered suffixes.

The next definition classifies suffixes and symbols of strings.
Definition 1 (L-type and S-type) For any string $T$, $T_n = \$ \text{ has type } S$. A suffix $T_i$ is an S-suffix if $T_i < T_{i+1}$, otherwise $T_i$ is an L-suffix. $T[i]$ has the type of $T_i$.

The suffixes can be classified in linear time by scanning $T$ once from right to left. The type of each suffix is stored in a bitmap of size $n$.

Note that, in a $c$-bucket, all L-suffixes precede to the S-suffixes.

Further, the classification of suffixes is refined as below:

Definition 2 (LMS-type) Let $T$ be a string. $T_i$ is an LMS-suffix if $T_i$ is an S-suffix and $T_{i-1}$ is an L-suffix.

Nong et al. [9] showed that the order of the LMS-suffixes is enough to induce the order of all suffixes.

SAIS works as follows:

SAIS framework:

1. Sort the LMS-suffixes. This step is explained below.

2. Insert the LMS-suffixes into their $c$-buckets in SA, without changing their order.

3. Induce L-suffixes by scanning SA from left to right: for each suffix $SA[i]$ if $T[SA[i] - 1]$ is L-type, insert $SA[i] - 1$ into the head of its bucket.

4. Induce S-suffixes by scanning SA from right to left: for each suffix $SA[i]$ if $T[SA[i] - 1]$ is S-type, insert $SA[i] - 1$ into the tail of its bucket.

We say that whenever a value is inserted in the head (or tail) of a bucket, the head (or tail) is increased (or decreased) by one.

In order to sort the LMS-suffixes in Step 1, $T[1,n]$ is divided (factorized) into LMS-substrings.

Definition 3 $T[i,j]$ is an LMS-substring if both $T_i$ and $T_j$ are LMS-suffixes, but no suffix between $i$ and $j$ has LMS-type. The last suffix $T_n$ is an LMS-substring.

Let $r_1^1, r_2^1, \ldots, r_n^1$ be the $n^1$ LMS-substrings of $T$ read from left-to-right. A modified version of SAIS is applied to sort the LMS-substrings. Starting from Step 2, $T[1,n]$ is scanned (right-to-left) and each unsorted LMS-suffix is inserted (bucket-sorted) regarding its first symbol at the tail of its $c$-bucket. Steps 3 and 4 work exactly the same. At the end, all LMS-substrings are sorted and stored in their corresponding $c$-buckets in SA.

Naming:

A name $v_i^1$ is assigned to each LMS-substring $r_i^1$ according to its lexicographical rank in $[1, \sigma^1]$, such that $v_i^1 < v_j^1$ if $r_i^1 < r_j^1$, $v_i^1 = v_j^1$ if $r_i^1 = r_j^1$ and $\sigma^1$ is the number of different LMS-substrings in $T$. In order to compute the names, each consecutive LMS-substrings in SA, say $r_i^1$ and $r_{i+1}^1$, are compared to determine if either $r_i^1 = r_{i+1}^1$ or $r_i^1 < r_{i+1}^1$. In the former case $v_i^1$ is named as $v_i^1$, whereas in the latter case $v_{i+1}^1$ is named as $v_i^1 + 1$. This procedure may be sped up by comparing the LMS-substrings first by symbol and then by type, with L-type symbols being smaller than S-type symbols in case of ties [18].
Recursive call:

A new (reduced) string \( T^1 = v_1^1 \cdot v_1^1 \cdots v_n^1 \) is created, whose length \( n^1 \) is at most \( n/2 \), and the alphabet size \( \sigma^1 \) is integer. If every \( v_i^1 \neq v_j^1 \) then all LMS-suffixes are already sorted. Otherwise, SAIS is recursively applied to sort all the suffixes of \( T^1 \). Nong et al. [9] showed that the relative order of the LMS-suffixes in \( T \) is the same as the order of the respective suffixes in \( T^1 \). Therefore, the order of all LMS-suffixes can be determined by the result of the recursive algorithm.

Grammar Compression by Induced Suffix Sorting

In this section we introduce the grammar compression by induced sorting (GCIS), which is based on SAIS.

First, we compute a context-free grammar \( G = (\Sigma, \Gamma, P, X_S) \) that generates only \( T[1, n] \). To do this we modify SAIS as follows.

Grammar construction:

Considering the \( j \)-th recursion level, in Step 1, after the input string \( T^j[1, n] \) is divided into the LMS-substrings \( r_1^j, r_2^j, \ldots, r_{n^j}^j \) and named into \( v_1^j, v_2^j, \ldots, v_{n^j}^j \), we create a new rule \( X_i \rightarrow \alpha_i \) for each different LMS-substring \( r_i^j = T^j[a, b] \) in the form \( r(v_i^j) \rightarrow T^j[a, b - 1] \), where \( r(v_i^j) = v_i^j + \sum_{k=1}^{j-1} \sigma^k \). Moreover, we create an additional rule \( r(0^j) \rightarrow T^j[1, j_1 - 1] \) for the prefix of \( T^j \) that is not included in the first LMS-substring \( r_1^j \).

The algorithm is called recursively with the reduced string \( T^{j+1} = v_1^{j+1} \cdot v_2^{j+1} \cdots v_{n^j}^{j+1} \) as input while \( \sigma^j < n^j \), that is, the LMS-substrings are not pairwise distinct. At the end, when \( \sigma^j = n^j \), we create the start symbol of \( G \) as being \( X_S \), such the production \( X_S \rightarrow r(0^j) \cdot r(v_1^j) \cdot r(v_2^j) \cdots r(v_{n^j}^j) \) generates only the original string \( T[1, n] \).

The algorithm stops after computing \( X_S \), since we are not interested in constructing the suffix array, we do not execute Steps 2, 3 and 4 of SAIS. The recursive calls return to the top level and we have computed a grammar \( G \) that generates only \( T[1, n] \).

Since for each LMS-substring a unique \( r(v_i^j) \) exists, there are no cycles in any derivations, and \( \ell(G) = T \), we have that \( G \) is a grammar that compresses \( T \) [19].

Grammar compression:

Consecutive entries in the set of productions \( P \) are likely to share a common prefix, since the LMS-substrings are given lexicographically ordered by SAIS. Therefore, each rule \( X_i \rightarrow \alpha_i \in P \) is encoded using two values \( (\ell_i, s(\alpha_i)) \), such that \( \ell_i \) encodes the length of longest common prefix \( (1 \operatorname{cp}) \) between \( \alpha_{i-1} \) and \( \alpha_i \), and the remaining symbols of \( \alpha_i \) are given by \( s(\alpha_i) = \alpha_i[\ell_i + 1, |\alpha_i|] \). This technique is known as Front-coding [20].

The computation of \( (\ell_i, s(\alpha_i)) \) is performed with no additional cost with a slight modification in the naming procedure of SAIS. Each consecutive LMS-substring in \( \text{SA} \), say \( r_{i-1}^j \) and \( r_i^j \) are compared first by symbol and then by type to check if either \( r_{i-1}^j = r_i^j \) or \( r_{i-1}^j < r_i^j \). In order to compute \( 1 \operatorname{cp}(r_{i-1}^j, r_i^j) \) we compare them only by
symbol until finding the first mismatch. The resulting order is the same with a small slowdown in the running time.

Computational cost:

GCIS runs in $O(n)$ time, since each step of the modified SAIS is linear and the length of the reduced string $T^j$ is at most $|T^{j-1}|/2$.

Implementation details

In this section we discuss implementation details of the GCIS encoding and decoding processes.

Encoding:

A rule $X_i$ is derived into a pair $\alpha_i = (\ell_i, s(\alpha_i))$, where $\ell$ equals $1\text{cp}(\alpha_{i-1}, \alpha_i)$ and $s(\alpha_i)$ corresponds to the remaining $\alpha_i[\ell_i + 1, |\alpha_i|]$ symbols. The $\ell$ values tend to be small and, considering the $j$-th recursion value, the sum of such values cannot be greater than $n^j$, since no two LMS-substrings overlap.

One can encode all $\ell$ values into a sequence of computer words $L$ by using Simple8b encoding [21]. This technique packs a number of small integers in a 64-bit word using the number of bits required by the largest integer. Basically it identifies a word with a 4-bit tag called selector, which specifies the number of integers encoded in a single word and the width of such integers. Simple8b also has specific selectors for a run consisting of zeroes. If a run of 240 or 120 zeros is encountered, it can be represented with a single 64 bit word. Table 1 contain all possible selector values, which reflects the possible arrangements of fixed-width integers storage in a single 64-bit word under this encoding scheme.

All $s(\alpha_i)$ are encoded in a single fixed-width integer array $R$, consisting of width $\lfloor \log(\alpha^j) \rfloor + 1$ bits. The length of each $s(\alpha_i)$ is also encoded using Simple8b into a word array $S$. The same observation of the $1\text{cp}$ sum can be done here: the sum of all $|s(\alpha_i)|$ is no larger than $n^j$.

A greedy strategy was employed to stop the recursion when the dictionary size of the $(j + 1)$-th level plus the size in bits of $T^{j+1}$ is bigger than the size in bits of $T^j$. In this situation, the computation done on the $j$-th level is discarded and the algorithm stops. When this condition is met, $\alpha^j < n^j$, but this does not interfere on the decoding algorithm.

Table 1: Simple8b possible arrangements [21].

| Selector value | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|----------------|---|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| Item width     | 0 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 10 | 12 | 15 | 20 | 30 | 60 |
| Group Size     | 240 | 120 | 60 | 30 | 20 | 15 | 12 | 10 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 |
| Wasted bits    | 60 | 60 | 0 | 0 | 0 | 0 | 0 | 4 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
Decoding:

The decoding process is done level-wise, starting from the last level, by decoding the right side of each rule. In the \(j\)-th level, the values \((x, y, z)\) from \(L\), \(R\) and \(S\) are decoded in a sequential way. In order to compute \(\alpha_{k+1}\) from \(\alpha_k\), the first \(x\) symbols of \(\alpha_k\) are copied to \(\alpha_{k+1}\) and the \(z\) symbols from \(R\), which correspond to the string \(y\), are copied to \(\alpha_{k+1}\) as well. A bitmap \(D\) is built to contain the length of all \(\alpha_i\) by using Rice-coding. With two \texttt{SELECT} operations it is possible to query the starting point of each \(\alpha_i\) in this array and the length \(|\alpha_i|\) in constant time using \(2n^j + o(n^j)\) bits, where \(j\) corresponds to the \(j\)-th recursive step of the grammar construction.

Once all rules are expanded into a fixed-width integer array of \(\lfloor \log(\sigma^j) \rfloor + 1\) bits, \(T^{j-1}\) can be decoded from \(T^j\). First, the right side of \(r(0^j)\) is copied into \(T^{j-1}\). Then, \(T^j\) is scanned in a left-to-right fashion and for each \(T^j[i]\) the algorithm copies a substring to \(T^{j-1}\) which equals the right side of \(r(T^j[i])\) and can be easily found with the bitmap \(D\) support.

Experiments

We compared GCIS with \texttt{RE-PAIR}\(^1\) and \texttt{7-ZIP}\(^2\) regarding Pizza\&Chili Repetitive Corpus\(^3\) under the subjects of compression ratio, compression and decompression running time. In particular, we used a space-efficient implementation of \texttt{RE-PAIR} by Wan [22], which encodes each rule with one integer plus few bits. GCIS was implemented in \texttt{C++11} using the Succinct Data Structure Library (SDSL) [23].

All experiments were conducted on machine with 2x \texttt{Intel(R) Xeon(R) CPU E5-2407 v2 @ 2.40GHz} CPUs and 256GB of RAM memory. The operating system used was based on the Debian GNU/Linux O.S. The input size of each experiment is given in the second column of Tables 2, 3 and 4.

Experimental results show that our algorithm is very effective at handling repetitive strings. GCIS presents a competitive compression ratio, compression and decompression time, being a real practical option when considering all those subjects simultaneously.

Compression and decompression:

Table 2 comprises the compression Ratio (\%), corresponding to the size of the compressed text over the original input size. \texttt{7-ZIP} presents the best compression ratio, except for \texttt{coreutils, fib41, rs} and \texttt{tm29}, where \texttt{RE-PAIR} outperforms it. Note that GCIS presents a competitive compression ratio compared to \texttt{RE-PAIR}.

Table 3 shows the compression time of each algorithm. GCIS is the fastest algorithm, except for \texttt{einstein.de, einstein.en} and \texttt{proteins}, where \texttt{7-ZIP} was the fastest. GCIS outperforms \texttt{RE-PAIR} and \texttt{7-ZIP} by a large margin in most cases, being up to 6.5 times faster than \texttt{RE-PAIR (tm29)} and up to 6.9 times faster than \texttt{7-ZIP (cere)}.

\(^1\)https://github.com/rwanwork/Re-Pair
\(^2\)http://p7zip.sourceforge.net/
\(^3\)http://pizzachili.dcc.uchile.cl/repcorpus.html
Table 2: Compression ratio regarding Pizzaz&Chili repetitive corpus.

| Pizza&Chili Repetitive Corpus | Input Size (MB) | GCIS | Re-PAIR | 7-ZIP |
|-------------------------------|----------------|------|---------|-------|
| cere                          | 461.29         | 3.76 | 1.86    | 1.82  |
| coreutils                     | 205.28         | 5.39 | 2.54    | 11.63 |
| dblp.xml.00001.1              | 104.86         | 0.43 | 0.19    | 0.16  |
| dblp.xml.00001.2              | 104.86         | 0.43 | 0.18    | 0.16  |
| dblp.xml.0001.1               | 104.86         | 0.84 | 0.46    | 0.20  |
| dblp.xml.0001.2               | 104.86         | 0.77 | 0.39    | 0.19  |
| dna.001.1                     | 104.86         | 3.55 | 2.43    | 0.51  |
| einstein.de.txt               | 92.76          | 0.31 | 0.16    | 0.11  |
| einstein.en.txt               | 467.63         | 0.20 | 0.10    | 0.07  |
| english.001.2                 | 104.86         | 4.17 | 2.41    | 0.55  |
| escherichiacoli               | 112.69         | 14.14| 9.60    | 6.56  |
| fib41                         | 267.91         | 0.03 | 0.00    | 0.36  |
| influenza                     | 154.81         | 4.76 | 3.26    | 1.65  |
| kernel                        | 257.96         | 2.37 | 1.10    | 0.82  |
| para                          | 429.27         | 4.98 | 2.74    | 2.39  |
| proteins.001.1                | 104.86         | 4.13 | 2.64    | 0.59  |
| rs.13                         | 216.75         | 0.02 | 0.00    | 0.16  |
| sources.001.2                 | 104.86         | 4.10 | 2.34    | 0.45  |
| tm29                          | 268.44         | 0.02 | 0.00    | 0.72  |
| world_leaders                 | 46.97          | 3.38 | 1.79    | 1.39  |

Table 4 presents the decompression time of each algorithm. 7-ZIP outperforms Re-PAIR and GCIS, except for fib41, rs and tm29, where Re-PAIR was the fastest. GCIS is up to 20 times slower than Re-PAIR and 7-ZIP (einstein.en), whereas Re-PAIR is up to 6.6 times slower than 7-ZIP (cere).

**Peak memory**

We evaluated the peak memory consumption of Re-PAIR and GCIS in compression and decompression procedures. 7-ZIP and was not evaluated since it require negligible amount of space when compressing or decompressing.

Figure 1a shows that GCIS requires five times less the space needed by Re-PAIR during compression. Since GCIS is based on SAIS, it requires $\approx 5 \times n$ bytes, for inputs with $n < 4$GB, whereas Re-PAIR requires $\approx 30 \times n$ bytes, becoming prohibitive when the input is large. In decompression, illustrated by 1b, Re-PAIR has a lower peak memory usage than GCIS, making the former more appealing when memory is limited.
| Pizza&Chili Repetitive Corpus | Compression Time (s) |
|-------------------------------|---------------------|
|                               | GCIS | Re-PAIR | 7-zip |
| cere                          | 461.29 | 100.61 | 464.62 | 693.10 |
| coreutils                     | 205.28 | 44.48  | 210.21 | 85.19  |
| dblp.xml.00001.1              | 104.86 | 21.34  | 71.85  | 25.63  |
| dblp.xml.00001.2              | 104.86 | 21.59  | 72.31  | 25.60  |
| dblp.xml.0001.1               | 104.86 | 21.21  | 72.35  | 25.79  |
| dblp.xml.0001.2               | 104.86 | 21.76  | 73.70  | 27.16  |
| dna.001.1                     | 104.86 | 19.48  | 73.83  | 63.56  |
| einstein.de.txt               | 92.76  | 22.48  | 62.17  | 16.26  |
| einstein.en.txt               | 467.63 | 135.19 | 338.30 | 85.02  |
| english.001.2                 | 104.86 | 27.79  | 93.61  | 41.36  |
| escherichiacoli               | 112.69 | 22.42  | 138.06 | 143.05 |
| fib41                         | 267.91 | 15.58  | 77.35  | 29.36  |
| influenza                     | 154.81 | 26.64  | 108.98 | 46.14  |
| kernel                        | 257.96 | 60.26  | 223.52 | 120.18 |
| para                          | 429.27 | 95.93  | 512.93 | 583.92 |
| proteins.001.1                | 104.86 | 29.05  | 82.86  | 21.27  |
| rs.13                         | 216.75 | 12.04  | 69.58  | 22.88  |
| sources.001.2                 | 104.86 | 23.56  | 85.69  | 31.16  |
| tm29                          | 268.44 | 14.33  | 92.70  | 39.11  |
| world_leaders                 | 46.97  | 5.98   | 23.57  | 9.26   |

Conclusions

In the article we introduced a new grammar-based compression algorithm, called GCIS, which is based on the induced suffix sorting framework of SAIS [9]. Experiments showed that GCIS is competitive compared to Re-Pair and 7-zip, being very effective at handling repetitive strings.

Future works:

As a future work, one can think of a GCIS/Re-Pair hybrid approach. The key idea is to encode the first recursive levels using GCIS and then shift to Re-Pair. While making the compression a little slower, this approach can make decompression faster while preserving a good compression ratio.

We remark that GCIS, as well as Re-Pair, can support extract random substrings $T[l, r]$ without decompressing the complete string $T[1, n]$, by storing additional data structures [8], whereas such operation is not possible for LZ77 based compressors [24]. We intend to implement this operation aiming at reducing its memory footprint. Also, an efficient way to search for a pattern in the compressed text is desirable.
Table 4: Decompression time regarding Pizzaz&Chili repetitive corpus.

| Pizza&Chili Repetitive Corpus | Input Size (MB) | GCIS  | Re-PAIR | 7-Zip |
|------------------------------|----------------|-------|---------|-------|
| cere                         | 461.29         | 18.88 | 13.31   | 2.01  |
| coreutils                    | 205.28         | 13.53 | 3.95    | 2.37  |
| dblp.xml.00001.1             | 104.86         | 5.61  | 0.82    | 0.34  |
| dblp.xml.00001.2             | 104.86         | 5.62  | 0.85    | 0.34  |
| dblp.xml.0001.1              | 104.86         | 5.58  | 0.85    | 0.34  |
| dblp.xml.0001.2              | 104.86         | 5.65  | 1.04    | 0.34  |
| dna.001.1                    | 104.86         | 6.31  | 1.75    | 0.37  |
| einstein.de.txt              | 92.76          | 5.57  | 0.45    | 0.29  |
| einstein.en.txt              | 467.63         | 29.40 | 2.70    | 1.43  |
| english.001.2                | 104.86         | 7.48  | 3.76    | 0.37  |
| escherichiacoli              | 112.69         | 7.49  | 3.36    | 0.87  |
| fib41                        | 267.91         | 11.55 | 0.53    | 1.09  |
| influenza                    | 154.81         | 9.16  | 1.09    | 0.67  |
| kernel                       | 257.96         | 16.50 | 5.96    | 0.94  |
| para                         | 429.27         | 19.18 | 12.88   | 2.16  |
| proteins.001.1               | 104.86         | 7.69  | 2.45    | 0.38  |
| rs.13                        | 216.75         | 9.19  | 0.43    | 0.71  |
| sources.001.2                | 104.86         | 6.93  | 3.21    | 0.36  |
| tm29                         | 268.44         | 10.26 | 0.53    | 1.16  |
| world_leaders                | 46.97          | 1.66  | 0.45    | 0.20  |

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Figure 1: Peak memory of GCIS and Re-Pair regarding compression and decompression.

(a) Memory Peak (MB) during compression.

(b) Memory Peak (MB) during decompression.

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