Strategies for Stable Merge Sorting

Abstract

We introduce new stable, natural merge sort algorithms, called 2-merge sort and $\alpha$-merge sort. We prove upper and lower bounds for several merge sort algorithms, including Timsort, Shiver’s sort, $\alpha$-stack sorts, and our new 2-merge and $\alpha$-merge sorts. The upper and lower bounds have the forms $c \cdot n \log m$ and $c \cdot n \log n$ for inputs of length $n$ comprising $m$ runs. For Timsort, we prove a lower bound of $(1.5 - o(1))n \log n$. For 2-merge sort, we prove optimal upper and lower bounds of approximately $(1.089 \pm o(1))n \log m$. We prove similar asymptotically matching upper and lower bounds for $\alpha$-merge sort, when $\varphi < \alpha < 2$, where $\varphi$ is the golden ratio. These merge strategies can be used for any stable merge sort, not just natural merge sorts.

The new 2-merge and $\alpha$-merge sorts have better worst-case merge cost upper bounds and are slightly simpler to implement than the widely-used Timsort; they also perform better in experiments.

1 Introduction

This paper studies stable merge sort algorithms, especially natural merge sorts. We will propose new strategies for the order in which merges are performed, and prove upper and lower bounds on the cost of several merge strategies. The first merge sort algorithm was proposed by von Neumann [10, p.159]: it works by splitting the input list into sorted sublists, initially possibly lists of length one, and then iteratively merging pairs of sorted lists, until the entire input is sorted. A sorting algorithm is stable if it preserves the relative order of elements which are not distinguished by the sort order. There are several methods of splitting the input into sorted sublists before starting the merging; a merge sort is called natural if it finds the sorted sublists by detecting consecutive runs of entries in the input which are already in sorted order. Natural merge sorts were first proposed by Knuth [10, p.160].

Like most sorting algorithms, the merge sort is comparison-based in that it works by comparing the relative order of pairs of entries in the input list. Information-theoretic considerations imply that any comparison-based sort algorithm must make at least $\log_2(n!) \approx n \log_2 n$ comparisons in the worst case. However, in many practical applications, the input is frequently already partially sorted. There are many adaptive sort algorithms which will detect this and run faster on inputs which are already partially sorted. Natural merge sorts are adaptive in this sense: they detect sorted sublists (called “runs”) in the input, and thereby reduce the cost of merging sublists. One
very popular stable natural merge sort is the eponymous Timsort of Tim Peters [17]. Timsort
extensively used, as it is included in Python, in the Java standard library, in GNU Octave, and
in the Android operating system. Timsort has worst-case runtime $O(n \log n)$, but is designed to
run substantially faster on inputs which are partially pre-sorted by using intelligent strategies to
determine the order in which merges are performed.

There is extensive literature on adaptive sorts: e.g., for theoretical foundations see [14, 7, 16, 15]
and for more applied investigations see [5, 9, 4, 21, 18]. The present paper will consider only stable,
natural merge sorts. As exemplified by the wide deployment of Timsort, these are certainly an
important class of adaptive sorts. We will consider the Timsort algorithm [17, 6], and related sorts
due to Shivers [19] and Auger-Nicaud-Pivoteau [1]. We will also introduce new algorithms, the
“2-merge sort” and the “$\alpha$-merge sort” for $\varphi < \alpha < 2$ where $\varphi$ is the golden ratio.

We focus on natural merge sorts, since they are so widely used. However, our central contribu-
tion is analyzing merge strategies and our results are applicable to any stable sorting algorithm that
generates and merges runs, including patience sorting [4], melsort [20, 13], and split sorting [12].

All the merge sorts we consider will use the following framework. (See Algorithm 1.) The
input is a list of $n$ elements, which without loss of generality may be assumed to be integers. The
first logical stage of the algorithm (following Knuth [10]) identifies maximal length subsequences
of consecutive entries which are in sorted order, either ascending or descending. The descending
subsequences are reversed, and this partitions the input into “runs” $R_1, \ldots, R_m$ of entries sorted
in non-decreasing order. The number of runs is $m$; the number of elements in a run $R$ is $|R|$. Thus
$\sum_i |R_i| = n$. It is easy to see that these runs may be formed in linear time and with linear number
of comparisons.

The merge sort algorithm processes the runs in left-to-right order starting with $R_1$. This permits
runs to be identified on-the-fly, only when needed. This means there is no need to allocate $O(m)$
additional memory to store the runs. This also may help reduce cache misses. On the other hand, it
means that the value $m$ is not known until the final run is formed; thus, the natural sort algorithms
do not use $m$ except as a stopping condition.

The runs $R_i$ are called original runs. The second logical stage of the natural merge sort algo-
rithms repeatedly merges runs in pairs to give longer and longer runs. (As already alluded to, the
first and second logical stages are interleaved in practice.) Two runs $A$ and $B$ can be merged in
linear time; indeed with only $|A| + |B| - 1$ many comparisons and $|A| + |B|$ many movements of
elements. The merge sort stops when all original runs have been identified and merged into a single
run.

Our mathematical model for the run time of a merge sort algorithm is the sum, over all merges
of pairs of runs $A$ and $B$, of $|A| + |B|$. We call the quantity the merge cost. In most situations,
the run time of a natural sort algorithm can be linearly bounded in terms of its merge cost. Our
main theorems are lower and upper bounds on the merge cost of several stable natural merge sorts.
Note that if the runs are merged in a balanced fashion, using a binary tree of height $\lceil \log m \rceil$, then
the total merge cost $\leq n \lceil \log m \rceil$. (We use log to denote logarithms base 2.) Using a balanced
binary tree of merges gives a good worst-case merge cost, but it does not take into account savings
that are available when runs have different lengths.\footnote{\cite{8} gives a different method of achieving merge cost $O(n \log m)$. Like the binary tree method, their method is not adaptive.} The goal is find adaptive stable natural merge sorts which can effectively take advantage of different run lengths to reduce the merge cost, but
which are guaranteed to never be much worse than the binary tree. Therefore, our preferred upper
bounds on merge costs are stated in the form $c \cdot n \log m$ for some constant $c$, rather than in the
form $c \cdot n \log n$.\footnote{\cite{8} gives a different method of achieving merge cost $O(n \log m)$. Like the binary tree method, their method is not adaptive.}
The merge cost ignores the $O(n)$ cost of forming the original runs $R_i$: this does not affect the asymptotic limit of the constant $c$.

Algorithm 1 shows the framework for all the merge sort algorithms we discuss. This is similar to what Auger et al. [1] call the “generic” algorithm. The input $S$ is a sequence of integers which is partitioned into monotone runs of consecutive members. The decreasing runs are inverted, so $S$ is expressed as a list $\mathcal{R}$ of increasing runs $R_1, \ldots, R_m$ called “original runs”. The algorithm maintains a stack $\mathcal{X}$ of runs $X_1, \ldots, X_\ell$, which have been formed from original runs $R_1, \ldots, R_k$. Each time through the loop, it either pushes the next original run, $R_{k+1}$, onto the stack $\mathcal{X}$, or it chooses a pair of adjacent runs $X_i$ and $X_{i+1}$ on the stack and merges them. The resulting run replaces $X_i$ and $X_{i+1}$ and becomes the new $X_i$, and the length of the stack decreases by one. The entries of the runs $X_i$ are stored in-place, overwriting the elements of the array which held the input $S$. Therefore, the stack needs to hold only the positions $p_i$ (for $i = 0, \ldots, \ell+1$) in the input array where the runs $X_i$ start, and thereby implicitly the lengths $|X_i|$ of the runs. We have $p_1 = 0$, pointing to the beginning of the input array, and for each $i$, we have $|X_i| = p_{i+1} - p_i$. The unprocessed part of $S$ in the input array starts at position $p_{\ell+1} = p_\ell + |X_\ell|$. If $p_{\ell+1} < n$, then it will be the starting position of the next original run pushed onto $\mathcal{X}$.

**Algorithm 1** The basic framework for all our merge algorithms.

$S$ is a sequence of integers of length $n$. $\mathcal{R}$ is the list of $m$ runs formed from $S$. $\mathcal{X}$ is a stack of runs. $X_i$ is the $i$-th member of $\mathcal{X}$, for $1 \leq i \leq \ell$, where $\ell$ is the number of members of $\mathcal{X}$. $X_\ell$ is the top member of the stack $\mathcal{X}$.

$k_1$ and $k_2$ are fixed (small) integers. The algorithm is $(k_1, k_2)$-aware.

Upon termination, $\mathcal{X}$ contains a single run $X_1$ which is the sorted version of $S$.

1: procedure MERGESORTFRAMEWORK($S, n$)  
2: $\mathcal{R} \leftarrow$ list of runs forming $S$  
3: $\mathcal{X} \leftarrow$ empty stack  
4: while $\mathcal{R} \neq \emptyset$ or $\mathcal{X}$ has $> 1$ member do  
5: choose to do either (A) or (B) for some $\ell-k_2 < i < \ell$, based on  
6: whether $\mathcal{R}$ is empty and on the values $|X_j|$ for $\ell-k_1 < j \leq \ell$  
7: (A) Remove the next run $R$ from $\mathcal{R}$ and push it onto $\mathcal{X}$.
8: This increments $\ell = |\mathcal{X}|$ by 1.  
9: (B) Replace $X_i$ and $X_{i+1}$ in $\mathcal{X}$ with Merge($X_i, X_{i+1}$).
10: This decrements $\ell = |\mathcal{X}|$ by 1.  
11: end choices  
12: end while  
13: Return $X_1$ as the sorted version of $S$.  
14: end procedure

Algorithm 1 is called $(k_1, k_2)$-aware since its choice of what to do is based on just the lengths of the runs in the top $k_1$ members of the stack $\mathcal{X}$, and since merges are only applied to runs in the top $k_2$ members of $\mathcal{X}$. (1] used the terminology “degree” instead of “aware”.) In all our applications, $k_1$ and $k_2$ are small numbers, so it is appropriate to store the runs in a stack. Usually $k_1 = k_2$, and we write “$k$-aware” instead of “$(k, k)$-aware”. To improve readability (and following [1]), we use the letters $W, X, Y, Z$ to denote the top four runs on the stack, $X_{\ell-3}, X_{\ell-2}, X_{\ell-1}, X_\ell$ respectively, (if they exist).² Table 1 shows the awareness values for the algorithms considered in this paper.

In all the sorting algorithms we consider, the height of the stack $\mathcal{X}$ will be small, namely

²[17] used “$A, B, C$” for “$X, Y, Z$”.

3
\[ \ell = O(\log n) \]. Since the stack needs only store the \( \ell + 1 \) values \( p_1, \ldots, p_{\ell+1} \), the memory requirements for the stack are minimal.

Timsort [17] uses a variety of techniques to speed up the basic framework of Algorithm 1. These include using an insertion sort to generate runs of a minimum length, choosing the minimum length so that \( m \) is likely to slightly less than a power of two, and using “galloping” to speed up merges. Timsort also identifies the original runs \( R_j \) on-the-fly, as needed. This, plus the fact that merges are done only on runs near the top of the stack, helps reduce cache misses as there is tendency for merges to work on recently used runs. (See [11] for other method for reducing cache misses in sorting algorithms.)

\( \text{Merge}(A,B) \) is the run obtained by merging the two runs \( A \) and \( B \). Timsort speeds up the computation of \( \text{Merge}(A,B) \) with “galloping” by using auxiliary memory to hold the shorter of \( A \) and \( B \). It would also be possible to perform merges in-place with no additional memory. Both approaches mean that the computation of \( \text{Merge}(A,B) \) takes time \( O(|A|+|B|) \). We shall use \( |A|+|B| \) as our mathematical model for the runtime of a merge, as this gives a simple, and broadly applicable, measure of the runtime of natural sorts.\(^3\)

\textbf{Definition 1.} The \textit{merge cost} of a merge sort algorithm on an input \( S \) is the sum of \( |A|+|B| \) taken over all merge operations \( \text{Merge}(A,B) \) performed. For \( X_i \) a run on the stack \( \mathcal{X} \) during the computation, the \textit{merge cost} of \( X_i \) is the sum of \( |A|+|B| \) taken over all merges \( \text{Merge}(A,B) \) used to combine runs that helped form \( X_i \).

In later sections, the notation \( w_{X_i} \) is used to denote the merge cost of the \( i \)-th entry \( X_i \) on the stack at a given time. Here “\( w \)” stands for “weight”. The notation \( |X_i| \) denotes the length of the run \( X_i \). We will use \( m_{X_i} \) to denote the number of original runs which were merged to form \( X_i \).

All of the optimizations used by Timsort mentioned above can be used equally well with any of the merge sort algorithms discussed in the present paper. In addition, they can be used with other sorting algorithms that generate and merge runs. These other algorithms include patience sort [4], melsort [20] (which is an extension of patience sort), the hybrid quicksort-melsort algorithm of [13], and split sort [12]. The merge cost as defined above applies equally well to all these algorithms. Thus, it gives a runtime measurement which applies to a broad range of sort algorithms that incorporate merges and which is largely independent of which optimizations are used.

Algorithm 1, like all the algorithms we discuss, only merges adjacent elements, \( X_i \) and \( X_{i+1} \), on the stack. This is necessary for the sort to be stable: If \( i < i'' < i' \) and two non-adjacent runs \( X_i \) and \( X_{i'} \) were merged, then we would not know how to order members occurring in both \( X_{i'} \) and \( X_{i''} \).

\(^3\) It is possible to use more sophisticated data structures which allow some merges to be performed in sublinear time; see for instance [3, 8]. These methods do not seem to be useful in practical applications, and would be difficult to mathematically model in any event. For this reason, we feel that the merge cost \( |A|+|B| \) is the best way to model the runtime of merge sort algorithms.
and $X_i \cup X_j$. The patience sort, melsort, and split sort can all readily be modified to be stable, and our results on merge costs can be applied to them.

Our merge strategies do not apply to non-stable merging, but Barbay and Navarro [2] have given an optimal method—based on Huffman codes—of merging for non-stable merge sorts in which merged runs do not need to be adjacent.

The known worst-case upper and lower bounds on stable natural merge sorts are listed in Table 2. The table expresses bounds in the strongest forms known. Since $m \leq n$, it is generally preferable to have upper bounds in terms of $n \log m$, and lower bounds in terms of $n \log n$.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Upper bound</th>
<th>Lower bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timsort (version in [6])</td>
<td>$O(n \log n)$ [1]</td>
<td>$1.5 \cdot n \log n$ [Theorem 3]</td>
</tr>
<tr>
<td>$\alpha$-stack sort</td>
<td>$O(n \log n)$ [1]</td>
<td>${c_\alpha \cdot n \log n$ [Theorem 8]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\omega(n \log m)$ [Theorem 9]</td>
</tr>
<tr>
<td>Shivers sort</td>
<td>$n \log n$ [19]</td>
<td>$\omega(n \log m)$ [Theorem 10]</td>
</tr>
<tr>
<td>2-merge sort</td>
<td>$c_2 \cdot n \log m$ [Theorem 15]</td>
<td>$c_2 \cdot n \log m$ [Theorem 22]</td>
</tr>
<tr>
<td>$\alpha$-merge sort</td>
<td>$c_\alpha \cdot n \log m$ [Theorem 14]</td>
<td>$c_\alpha \cdot n \log m$ [Theorem 21]</td>
</tr>
</tbody>
</table>

Table 2: Upper and lower bounds on the merge cost of various algorithms. For more precise statements, see the theorems. The results hold for $\varphi < \alpha \leq 2$; for these values, $c_\alpha$ is defined by equation (2) and satisfies $1.042 < c_\alpha < 1.089$. In particular, $c_2 = 3/\log(27/4) \approx 1.08897$. All bounds are asymptotic; that is, they are correct up to a multiplicative factor of $1 \pm o(1)$. For this reason, the upper and lower bounds in the last two lines of the table are not exactly matching.

The table lists 2-merge sort and $\alpha$-merge sort on separate lines since the 2-merge sort is slightly simpler than the $\alpha$-merge sort. In addition, our proof of the upper bound for the 2-merge sort algorithm is substantially simpler than our proof for the $\alpha$-merge sort.

The main results of the paper are those listed in the final two lines of Table 2. Theorem 22 proves that the merge cost of 2-merge sort is at most $(d_2 + c_2 \log m) \cdot n$, where $d_2 \approx 1.911$ and $c_2 \approx 1.089$: these are very tight bounds, and the value for $c_2$ is optimal by Theorem 15. It is also substantially better than the worst-case merge cost for Timsort proved in Theorem 3. Similarly for $\varphi < \alpha < 2$, Theorem 22 proves an upper bound of $(d_\alpha + c_\alpha \log m) \cdot n$. The values for $c_\alpha$ are optimal by Theorem 14; however, our values for $d_\alpha$ have unbounded limit $\lim_{\alpha \to \varphi^+} d_\alpha$ and we conjecture this is not optimal.

We only analyze $\alpha$-merge sorts with $\alpha > \varphi$. It is an open problem to extend our algorithms to the case of $\alpha < \varphi$; we expect that this will require $k$-aware algorithms with $k > 3$.

The outline of the paper is as follows. Section 2 describes Timsort, and proves the lower bound on its merge cost. Section 3 discusses the $\alpha$-stack sort algorithms, and gives lower bounds on their merge cost. Section 4 describes the Shivers sort, and gives a simplified proof of the $n \log n$ upper bound of [19]. Section 5 is the core of the paper and describes the new 2-merge sort and $\alpha$-merge sort. We first prove the lower bounds on their merge cost, and finally prove the corresponding upper bounds. Section 6 gives some experimental results on various kinds of randomly generated data. All these sections can be read independently of each other. The paper concludes with discussion of open problems.


2 Timsort lower bound

Algorithm 2 is the Timsort algorithm as defined by [6] improving on [17]. The algorithm uses the convention that $W,X,Y,Z$ are the top four elements on the stack $\mathcal{X}$. A command “Merge $Y$ and $Z$” creates a single run which replaces both $Y$ and $Z$ in the stack; at the same time, the current third member on the stack, $X$, becomes the new second member on the stack and is now designated $Y$. Similarly, the current $W$ becomes the new $X$, etc. Likewise, the command “Merge $X$ and $Y$” merges the second and third elements at the top of $\mathcal{X}$; those two elements are removed from $\mathcal{X}$ and replaced by the result of the merge.

Algorithm 2 The Timsort algorithm. $W,X,Y,Z$ denote the top four elements of the stack $\mathcal{X}$. A test involving a stack member that does not exist evaluates as “False”. For example, $|X| < |Z|$ evaluates as false when $|X| < 3$ and $X$ does not exist.

1: procedure TimSort($S$, $n$)
2: $\mathcal{R} \leftarrow$ run decomposition of $S$
3: $\mathcal{X} \leftarrow \emptyset$
4: while $\mathcal{R} \neq \emptyset$ do
5: Remove the next run $R$ from $\mathcal{R}$ and push it onto $\mathcal{X}$
6: loop
7: if $|X| < |Z|$ then
8: Merge $X$ and $Y$
9: else if $|X| \leq |Y| + |Z|$ then
10: Merge $Y$ and $Z$
11: else if $|W| \leq |X| + |Y|$ then
12: Merge $Y$ and $Z$
13: else if $|Y| \leq |Z|$ then
14: Merge $Y$ and $Z$
15: else
16: Break out of the loop
17: end if
18: end loop
19: end while
20: while $|\mathcal{X}| \geq 1$ do
21: Merge $Y$ and $Z$
22: end while
23: end procedure

Timsort was designed so that the stack has size $O(\log n)$, and so that the total running time will be $O(n \log n)$. A detailed proof of the run time was first given by Auger et al. [1]:

Theorem 2 ([1]). The merge cost of Timsort is $O(n \log n)$.

Auger et al. [1] did not compute the constant implicit in their proof of the upper bound of Theorem 2; but it is approximately equal to $3/\log \varphi \approx 4.321$. We prove a corresponding lower bound:

Theorem 3. The worst-case merge cost of the Timsort algorithm on inputs of length $n$ which decompose into $m$ original runs is $\geq (1.5-o(1)) \cdot n \log n$. Hence it is also $\geq (1.5-o(1)) \cdot n \log m$.

In other words, for any $c < 1.5$, there are inputs to Timsort with arbitrarily large values for $n$ (and $m$) so that Timsort has merge cost $> c \cdot n \log n$. We conjecture that Theorem 2 is nearly optimal:
Conjecture 4. The merge cost of Timsort is bounded by \((1.5+o(1)) \cdot n \log m\).

Note that it is still open whether Timsort has runtime \(O(n \log m)\) at all.

**Proof of Theorem 3.** We must define inputs that cause Timsort to take time close to \(1.5n \log n\). As always, \(n \geq 1\) is the length of the input \(S\) to be sorted. We define \(R_{\text{tim}}(n)\) to be a sequence of run lengths so that \(R_{\text{tim}}(n)\) equals \(\langle n_1, n_2, \ldots, n_m \rangle\) where each \(n_i > 0\) and \(\sum_{i=1}^{m} n_i = n\). Furthermore, we will have \(m \leq n \leq 3m\), so that \(\log n = \log m + O(1)\). The notation \(R_{\text{tim}}\) is reminiscent of \(R\), but \(R\) is a sequence of runs whereas \(R_{\text{tim}}\) is a sequence of run lengths. Since the merge cost of Timsort depends only on the lengths of the runs, it is more convenient to work directly with the sequence of run lengths.

The sequence \(R_{\text{tim}}(n)\), for \(1 \leq n\), is defined as follows. First, for \(n \leq 3\), \(R_{\text{tim}}(n)\) is the sequence \(\langle n \rangle\), i.e., representing a single run of length \(n\). Let \(n' = \lfloor n/2 \rfloor\). For even \(n \geq 4\), we have \(n = 2n'\) and define \(R_{\text{tim}}(n)\) to be the concatenation of \(R_{\text{tim}}(n')\), \(R_{\text{tim}}(n'-1)\) and \(\langle 1 \rangle\). For odd \(n \geq 4\), we have \(n = 2n'+1\) and define \(R_{\text{tim}}(n)\) to be the concatenation of \(R_{\text{tim}}(n')\), \(R_{\text{tim}}(n'-1)\) and \(\langle 2 \rangle\).

We claim that for \(n \geq 4\), Timsort operates with run lengths \(R_{\text{tim}}(n)\) as follows: The first phase processes the runs from \(R_{\text{tim}}(n')\) and merges them into a single run of length \(n'\) which is the only element of the stack \(X\). The second phase processes the runs from \(R_{\text{tim}}(n'-1)\) and merges them also into a single run of length \(n'-1\); at this point the stack contains two runs, of lengths \(n'\) and \(n'-1\). Since \(n'-1 < n'\), no further merge occurs immediately. Instead, the final run is loaded onto the stack: it has length \(n''\) equal to either 1 or 2. Now \(n' \leq n'-1 + n''\) and the test \(|X| \leq |Y| + |Z|\) on line 9 of Algorithm 2 is triggered, so Timsort merges the top two elements of the stack, and then the test \(|Y| \leq |Z|\) causes the merge of the final two elements of the stack.

This claim follows from Claim 5. We say that the stack \(X\) is stable if none of the tests on lines 7,9,11,13, of Algorithm 2 hold.

**Claim 5.** Suppose that \(R_{\text{tim}}(n)\) is the initial subsequence of a sequence \(R'\) of run lengths, and that Timsort is initially started with run lengths \(R'\) either (a) with the stack \(X\) empty or (b) with the top element of \(X\) a run of length \(n_1 > n\) and the second element of \(X\) (if it exists) a run of length \(n_1 > n_0 + n\). Then Timsort will start by processing exactly the runs whose lengths are those of \(R_{\text{tim}}(n)\), merging them into a single run which becomes the new top element of \(X\). Timsort will do this without performing any merge of runs that were initially in \(X\) and without (yet) processing any of the remaining runs in \(R'\).

Claim 5 is proved by induction on \(n\). The base case, where \(n \leq 3\), is trivial since with \(X\) stable, Timsort immediately reads in the first run from \(R'\). The case of \(n \geq 4\) uses the induction hypothesis twice, since \(R_{\text{tim}}(n)\) starts off with \(R_{\text{tim}}(n')\) followed by \(R_{\text{tim}}(n'-1)\). The induction hypothesis applied to \(n'\) implies that the runs of \(R_{\text{tim}}(n')\) are first processed and merged to become the top element of \(X\). The stack elements \(X, Y, Z\) have lengths \(n_1, n_0, n'\) (if they exist), so the stack is now stable. Now the induction hypothesis for \(n'-1\) applies, so Timsort next loads and merges the runs of \(R_{\text{tim}}(n'-1)\). Now the top stack elements \(W, X, Y, Z\) have lengths \(n_1, n_0, n', n'-1\) and \(X\) is again stable. Finally, the single run of length \(n''\) is loaded onto the stack. This triggers the test \(|X| \leq |Y| + |Z|\), so the top two elements are merged. Then the test \(|Y| \leq |Z|\) is triggered, so the top two elements are again merged. Now the top elements of the stack (those which exist) are runs of length \(n_1, n_0, n\), and Claim 5 is proved.

Let \(c(n)\) be the merge cost of the Timsort algorithm on the sequence \(R_{\text{tim}}(n)\) of run lengths. The two merges described at the end of the proof of Claim 5 have merge cost \((n'-1) + n''\) plus
\(n' + (n' - 1) + n'' = n\). Therefore, for \(n > 3\), (1) satisfies
\[
c(n) = \begin{cases} 
c(n') + c(n' - 1) + \frac{3}{2}n & \text{if } n \text{ is even} \\
c(n') + c(n' - 1) + \frac{3}{2}n + \frac{1}{2} & \text{if } n \text{ is odd.}
\end{cases}
\]

Also, \(c(1) = c(2) = c(3) = 0\) since no merges are needed. Equation (1) can be summarized as
\[
c(n) = c([n/2]) + c([n/2] - 1) + \frac{3}{2}n + \frac{1}{2}(n \mod 2).
\]

The function \(n \mapsto \frac{3}{2}n + \frac{1}{2}(n \mod 2)\) is strictly increasing. From this, it is easy to prove by induction that \(c(n)\) is strictly increasing for \(n \geq 3\). So \(c([n/2]) > c([n/2] - 1)\), and thus \(c(n) \geq 2c([n/2] - 1) + \frac{3}{2}n\) for all \(n > 3\).

For \(x \in \mathbb{R}\), define \(b(x) = c([x-3])\). Since \(c(n)\) is nondecreasing, so is \(b(x)\). Then
\[
b(x) = c([x-3]) \geq 2c(([x-3]/2) - 1) + \frac{3}{2}(x-3)
\]
\[
\geq 2c([x/2] - 3) + \frac{3}{2}(x-3) = 2b(x/2) + \frac{3}{2}(x-3).
\]

**Claim 6.** For all \(x \geq 3\), \(b(x) \geq \frac{3}{2} \cdot [x([\log x] - 2) - x + 3]\).

We prove the claim by induction, namely by induction on \(n\) that it holds for all \(x < n\). The base case is when \(3 \leq x < 8\) and is trivial since the lower bound is negative and \(b(x) \geq 0\). For the induction step, the claim is known to hold for \(x/2\). Then, since \(\log(x/2) = (\log x) - 1\),
\[
b(x) \geq 2 \cdot b(x/2) + \frac{3}{2}(x-3)
\]
\[
\geq 2 \cdot \left( \frac{3}{2} \cdot [x/2([\log x] - 3) - x/2 + 3] \right) + \frac{3}{2}(x-3)
\]  
\[
= \frac{3}{2} \cdot [x([\log x] - 2) - x + 3]
\]
proving the claim.

Claim 6 implies that \(c(n) = b(n+3) \geq (\frac{3}{2} - o(1)) \cdot n \log n\). This proves Theorem 3.

## 3 The \(\alpha\)-stack sort

Augur-Nicaud-Pivoteau [1] introduced the \(\alpha\)-stack sort as a 2-aware stable merge sort; it was inspired by Timsort and designed to be simpler to implement and to have a simpler analysis. (The algorithm (e2) of [21] is the same as our \(\alpha\)-stack sort with \(\alpha = 2\).) We let \(\alpha > 1\) be a constant.

The \(\alpha\)-stack sort is shown in Algorithm 3. It makes less effort than Timsort to optimize the order of merges: up until the run decomposition is exhausted, its only merge rule is that \(Y\) and \(Z\) are merged whenever \(|Y| \leq \alpha|Z|\). An \(O(n \log n)\) upper bound on its runtime is given by the next theorem.

**Theorem 7** ([1]). Fix \(\alpha > 1\). The merge cost for the \(\alpha\)-stack sort is \(O(n \log n)\).

[1] did not explicitly mention the constant implicit in this upper bound, but their proof establishes a constant equal to approximately \((1+\alpha)/\log \alpha\). For instance, for \(\alpha = 2\), the merge cost is bounded by \((3 + o(1))n \log n\). The constant is minimized at \(\alpha \approx 3.591\), where is it approximately 2.489.
Algorithm 3 The α-stack sort. α is a constant > 1.

1: procedure α-stack(S, n)
2: \( R \leftarrow \) run decomposition of S
3: \( X \leftarrow \emptyset \)
4: while \( R \neq \emptyset \) do
5: \( \) Remove the next run \( R \) from \( R \) and push it onto \( X \)
6: while \( |Y| \leq \alpha |Z| \) do
7: \( \) Merge \( Y \) and \( Z \)
8: end while
9: end while
10: while \( |X| \geq 1 \) do
11: \( \) Merge \( Y \) and \( Z \)
12: end while
13: end procedure

Theorem 8. Let \( 1 < \alpha \). The worst-case merge cost of the α-stack sort on inputs of length \( n \) is
\[ \geq (c_{\alpha} - o(1)) \cdot n \log n, \]
where \( c_{\alpha} \) equals 
\[ \frac{\alpha + 1}{(\alpha+1) \log(\alpha+1) - \alpha \log(\alpha)} \].

The proof of Theorem 8 is postponed until Theorem 14 proves a stronger lower bound for α-merge sorts; the same construction works to prove both theorems. The value \( c_2 \approx 1.089 \); this is is discussed more in Section 5.

The lower bound of Theorem 8 is not very strong since the constant is close to 1. In fact, since a binary tree of merges gives a merge cost of \( n \lceil \log m \rceil \), it is more relevant to give upper and lower bounds in terms of \( O(n \log m) \) instead of \( O(n \log n) \). The next theorem shows that α-stack sort can be very far from optimal in this respect.

Theorem 9. Let \( 1 \leq \alpha \). The worst-case merge cost of the α-stack sort on inputs of length \( n \) which decompose into \( m \) original runs is \( \omega(n \log m) \).

In other words, for any \( c > 0 \), there are inputs with arbitrarily large values for \( n \) and \( m \) so that α-stack sort has merge cost > \( c \cdot n \log m \).

Proof. Let \( s \) be the least integer such that \( 2^s \geq \alpha \). Let \( R_{\text{ast}}(m) \) be the sequence of run lengths
\[ \langle 2^{(m-1) \cdot s} - 1, 2^{(m-2) \cdot s} - 1, \ldots, 2^{3s} - 1, 2^{2s} - 1, 2^{s} - 1, 2^{m-s} \rangle. \]

\( R_{\text{ast}}(m) \) describes \( m \) runs whose lengths sum to \( n = 2^{m-s} + \sum_{i=1}^{m-1} (2^i \cdot s - 1) \), so \( 2^{m-s} < n < 2^{m-s+1} \). Since \( 2^s \geq \alpha \), the test \( |Y| \leq \alpha |Z| \) on line 6 of Algorithm 3 is triggered only when the run of length \( 2^{m-s} \) is loaded onto the stack \( X \); once this happens the runs are all merged in order from right-to-left. The total cost of the merges is \( (m-1) \cdot 2^{m-s} + \sum_{i=1}^{m-1} i \cdot (2^i \cdot s - 1) \) which is certainly greater than \( (m-1) \cdot 2^{m-s} \). Indeed, that comes from the fact that the final run in \( R_{\text{ast}}(m) \) is involved in \( m-1 \) merges. Since \( n < 2 \cdot 2^{m-s} \), the total merge cost is greater than \( \frac{n}{2} (m-1) \), which is \( \omega(n \log m) \).

4 The Shivers merge sort

The 2-aware Shivers sort [19], shown in Algorithm 4, is similar to the 2-stack merge sort, but with a modification that makes a surprising improvement in the bounds on its merge cost. Although never published, this algorithm was presented in 1999.
Algorithm 4 The Shivers sort.

1: procedure ssort($S$, $n$)
2:   $R \leftarrow$ run decomposition of $S$
3:   $X \leftarrow \emptyset$
4:   while $R \neq \emptyset$
5:       Remove the next run $R$ from $R$ and push it onto $X$
6:       while $2^\lfloor \log |Y| \rfloor \leq |Z|$ do
7:           Merge $Y$ and $Z$
8:       end while
9:   end while
10:   while $|X| \geq 1$
11:       Merge $Y$ and $Z$
12:   end while
13: end procedure

The only difference between the Shivers sort and the 2-stack sort is the test used to decide when to merge. Namely, line 6 tests $2^\lfloor \log |Y| \rfloor \leq |Z|$ instead of $|Y| \leq 2 \cdot |Z|$. Since $2^\lfloor \log |Y| \rfloor$ is $|Y|$ rounded down to the nearest power of two, this is somewhat like an $\alpha$-sort with $\alpha$ varying dynamically in the range $[1, 2)$.

The Shivers sort has the same undesirable lower bound as 2-sort in terms of $\omega(n \log m)$:

**Theorem 10.** The worst-case merge cost of the Shivers sort on inputs of length $n$ which decompose into $m$ original runs is $\omega(n \log m)$.

*Proof.* This is identical to the proof of Theorem 9. We now let $R_{sh}(m)$ be the sequence of run lengths

$$\langle 2^{m-1}-1, 2^{m-2}-1, \ldots, 7, 3, 1, 2^m \rangle,$$

and argue as before. □

**Theorem 11 ([19]).** The merge cost of Shivers sort is $(1+o(1))n \log n$.

We present a proof which is simpler than that of [19]. The proof of Theorem 11 assumes that at a given point in time, the stack $X$ has $\ell$ elements $X_1, \ldots, X_\ell$, and uses $w_{X_i}$ to denote the merge cost of $X_i$. We continue to use the convention that $W, X, Y, Z$ denote $X_{\ell-3}, X_{\ell-2}, X_{\ell-1}, X_\ell$ if they exist.

*Proof.* Define $k_{X_i}$ to equal $\lfloor \log |X_i| \rfloor$. Obviously, $|X_i| \geq 2^{k_{X_i}}$. The test on line 6 works to maintain the invariant that each $|X_{i+1}| < 2^{k_{X_i}}$ or equivalently $k_{i+1} < k_i$. Thus, for $i < \ell-1$, we always have $|X_{i+1}| < 2^{k_{X_i}}$ and $k_{i+1} < k_i$. This condition can be momentarily violated for $i = \ell-1$, i.e. if $|Z| \geq 2^{k_Y}$ and $k_Y \leq k_Z$, but then the Shivers sort immediately merges $Y$ and $Z$.

As a side remark, since each $k_{i+1} < k_i$ for $i \leq \ell-1$, since $2^{k_1} \leq |X_1| \leq n$, and since $X_{\ell-1} \geq 1 = 2^0$, the stack height $\ell$ is $\leq 2 + \log n$. (In fact, a better analysis shows it is $\leq 1 + \log n$.)

**Claim 12.** Throughout the execution of the main loop (lines 4-9), the Shivers sort satisfies

a. $w_{X_i} \leq k_{X_i} \cdot |X_i|$, for all $i \leq \ell$,

b. $w_Z \leq k_Y \cdot |Z|$, i.e., $w_{X_\ell} \leq k_{X_{\ell-1}} \cdot |X_\ell|$, if $\ell > 1$. 

10
When \( i = \ell \), a. says \( w_Z \leq k_Z |Z| \). Since \( k_Z \) can be less than or greater than \( k_Y \), this neither implies, nor is implied by, b.

The lemma is proved by induction on the number of updates to the stack \( \mathcal{X} \) during the loop. Initially \( \mathcal{X} \) is empty, and a. and b. hold trivially. There are two induction cases to consider. The first case is when an original run is pushed onto \( \mathcal{X} \). Since this run, namely \( Z \), has never been merged, its weight is \( w_Z = 0 \). So b. certainly holds. For the same reason and using the induction hypothesis, a. holds. The second case is when \( 2^{k_Y} \leq |Z| \), so \( k_Y \leq k_Z \), and \( Y \) and \( Z \) are merged; here \( \ell \) will decrease by 1. The merge cost \( w_{YZ} \) of the combination of \( Y \) and \( Z \) equals \( |Y| + |Z| + w_Y + w_Z \), so we must establish two things:

a'. \( |Y| + |Z| + w_Y + w_Z \leq k_Y Z \cdot (|Y| + |Z|) \), where \( k_{YZ} = \lfloor \log (|Y| + |Z|) \rfloor \).

b'. \( |Y| + |Z| + w_Y + w_Z \leq k_X \cdot (|Y| + |Z|) \), if \( \ell > 2 \).

By induction hypotheses \( w_Y \leq k_Y |Y| \) and \( w_Z \leq k_Y |Z| \). Thus the lefthand sides of a'. and b'. are \( \leq (k_Y + 1) \cdot (|Y| + |Z|) \). As already discussed, \( k_Y < k_X \), therefore condition b. implies that b'. holds. And since \( 2^{k_Y} \leq |Z| \), \( k_Y < k_{YZ} \), so condition a. implies that a'. also holds. This completes the proof of Claim 12.

Claim 12 implies that the total merge cost incurred at the end of the main loop incurred is \( \leq \sum_i w_{X_i} \leq \sum_i k_i |X_i| \). Since \( \sum_i X_i = n \) and each \( k_i \leq \log n \), the total merge cost is \( \leq n \log n \).

We now upper bound the total merge cost incurred during the final loop on lines 10-12. When first reaching line 10, we have \( k_{i+1} < k_i \) for all \( i \leq \ell - 1 \) hence \( k_i < k_1 + 1 - i \) and \( |X_i| < 2^{k_1 + 2 - i} \) for all \( i \leq \ell \). The final loop then performs \( \ell - 1 \) merges from right to left. Each \( X_i \) for \( i < \ell \) participates in \( i \) merge operations and \( X_\ell \) participates in \( \ell - 1 \) merges. The total merge cost of this is less than \( \sum_{i=1}^{\ell} i \cdot |X_i| \). Note that

\[
\sum_{i=1}^{\ell} i \cdot |X_i| < 2^{k_1 + 2} \cdot \sum_{i=1}^{\ell} i \cdot 2^{-i} < 2^{k_1 + 2} \cdot 2 = 8 \cdot 2^{k_1} \leq 8n,
\]

where the last inequality follows by \( 2^{k_1} \leq |X_1| \leq n \). Thus, the final loop incurs a merge cost \( O(n) \), which is \( o(n \log n) \).

Therefore the total merge cost for the Shivers sort is bounded by \( n \log n + o(n \log n) \).

\( \square \)

5 The 2-merge and \( \alpha \)-merge sorts

This section introduces our new merge sorting algorithms, called the “2-merge sort” and the “\( \alpha \)-merge sort”, where \( \varphi < \alpha < 2 \) is a fixed parameter. These sorts are 3-aware, and this enables us to get algorithms with merge costs \((c_\alpha \pm o(1)) \log n \log m\). The idea of the \( \alpha \)-merge sort is to combine the construction with the 2-stack sort, with the idea from Timsort of merging \( X \) and \( Y \) instead of \( Y \) and \( Z \) whenever \( |X| < |Z| \). But unlike the Timsort algorithm shown in Algorithm 2, we are able to use a 3-aware algorithm instead of a 4-aware algorithm. In addition, our merging rules are simpler, and our provable upper bounds are tighter. Indeed, our upper bounds for \( \varphi < \alpha \leq 2 \) are of the form \((c_\alpha + o(1)) \cdot n \log m\) with \( c_\alpha \leq c_2 \approx 1.089 \). Although we conjecture Timsort has an upper bound of \( O(n \log m) \), we have not been able to prove it, and the multiplicative constant for any such bound must be at least 1.5 by Theorem 3.

Algorithms 5 and 6 show the 2-merge sort and \( \alpha \)-merge sort algorithms. Note that the 2-merge sort is almost, but not quite, the specialization of the \( \alpha \)-merge sort to the case \( \alpha = 2 \). The difference is that line 6 of the 2-merge sort has a simpler \textbf{while} test than the corresponding line in the \( \alpha \)-merge sort. As will be shown by the proof of Theorem 22, the fact that Algorithm 5 uses this simpler
while test makes no difference to which merge operations are performed; in other words, it would be redundant to test the condition $|X| < 2|Y|$.  

The 2-merge sort can also be compared to the $\alpha$-stack sort shown in Algorithm 3. The main difference is that the merge of $Y$ and $Z$ on line 7 of the $\alpha$-stack sort has been replaced by the lines 7-11 of the 2-merge which conditionally merge $Y$ with either $X$ or $Z$. For the 2-merge sort (and the $\alpha$-merge sort), the run $Y$ is never merged with $Z$ if it could instead be merged with a shorter $X$. The other, perhaps less crucial, difference is that the weak inequality test on line 6 in the $\alpha$-stack sort has been replaced with a strict inequality test on line 6 in the $\alpha$-merge sort. We have made this change since it seems to make the 2-merge sort more efficient, for instance when all original runs have the same length.

**Algorithm 5** The 2-merge sort.

<table>
<thead>
<tr>
<th>Line</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:</td>
<td>procedure 2-MERGE$(S, n)$</td>
</tr>
<tr>
<td>2:</td>
<td>$R \leftarrow$ run decomposition of $S$</td>
</tr>
<tr>
<td>3:</td>
<td>$\mathcal{X} \leftarrow \emptyset$</td>
</tr>
<tr>
<td>4:</td>
<td>while $R \neq \emptyset$ do</td>
</tr>
<tr>
<td>5:</td>
<td>Remove the next run $R$ from $R$ and push it onto $\mathcal{X}$</td>
</tr>
<tr>
<td>6:</td>
<td>while $</td>
</tr>
<tr>
<td>7:</td>
<td>if $</td>
</tr>
<tr>
<td>8:</td>
<td>Merge $X$ and $Y$</td>
</tr>
<tr>
<td>9:</td>
<td>else</td>
</tr>
<tr>
<td>10:</td>
<td>Merge $Y$ and $Z$</td>
</tr>
<tr>
<td>11:</td>
<td>end if</td>
</tr>
<tr>
<td>12:</td>
<td>end while</td>
</tr>
<tr>
<td>13:</td>
<td>end while</td>
</tr>
<tr>
<td>14:</td>
<td>while $</td>
</tr>
<tr>
<td>15:</td>
<td>Merge $Y$ and $Z$</td>
</tr>
<tr>
<td>16:</td>
<td>end while</td>
</tr>
<tr>
<td>17:</td>
<td>end procedure</td>
</tr>
</tbody>
</table>

We will concentrate mainly on the cases for $\varphi < \alpha \leq 2$ where $\varphi \approx 1.618$ is the golden ratio. Values for $\alpha > 2$ do not seem to give useful merge sorts; our upper bound proof does not work for $\alpha \leq \varphi$.

**Definition 13.** Let $\alpha \geq 1$, the constant $c_\alpha$ is defined by

$$c_\alpha = \frac{\alpha + 1}{(\alpha + 1) \log(\alpha + 1) - \alpha \log(\alpha)}. \quad (2)$$

For $\alpha = 2$, $c_2 = 3/\log(27/4) \approx 1.08897$. For $\alpha = \varphi$, $c_\varphi \approx 1.042298$. For $\alpha > 1$, $c_\alpha$ is strictly increasing as a function of $\alpha$. Thus, $1.042 < c_\alpha < 1.089$ when $\varphi < \alpha \leq 2$.

The next four subsections give nearly matching upper and lower bounds for the worst-case run time of the 2-merge sort and the $\alpha$-merge sort for $\varphi < \alpha < 2$.

### 5.1 Lower bound for 2-merge sort and $\alpha$-merge sort

**Theorem 14.** Fix $\alpha > 1$. The worst-case merge cost of the $\alpha$-merge sort algorithm is $\geq (c_\alpha - o(1))n \log n$.

The corresponding theorem for $\alpha = 2$ is:
Algorithm 6 The α-merge sort. α is a constant such that ϕ < α < 2.

1: procedure α-merge(S, n)
2: \( \mathcal{R} \leftarrow \text{run decomposition of } S \)
3: \( \mathcal{X} \leftarrow \emptyset \)
4: while \( \mathcal{R} \neq \emptyset \) do
5: Remove the next run \( R \) from \( \mathcal{R} \) and push it onto \( \mathcal{X} \)
6: while \( |Y| < \alpha |Z| \) or \( |X| < \alpha |Y| \) do
7: if \( |X| < |Z| \) then
8: Merge \( X \) and \( Y \)
9: else
10: Merge \( Y \) and \( Z \)
11: end if
12: end while
13: end while
14: while \( |\mathcal{X}| \geq 1 \) do
15: Merge \( Y \) and \( Z \)
16: end while
17: end procedure

Theorem 15. The worst-case merge cost of the 2-merge sort algorithm is \( \geq (c_2 - o(1))n \log n \), where \( c_2 = 3 / \log(27/4) \approx 1.08897 \)

The proof of Theorem 14 also establishes Theorem 8, as the same lower bound construction works for both α-stack sort and α-merge sort. The only difference is that part d. of Claim 17 is used instead of part c. In addition, the proof of Theorem 14 also establishes Theorem 15; indeed, exactly the same proof applies verbatim, just uniformly replacing “α” with “2”.

Proof of Theorem 14. Fix \( \alpha > 1 \). For \( n \geq 1 \), we define a sequence \( \mathcal{R}_{\alpha m}(n) \) of run lengths that will establish the lower bound. Define \( N_0 \) to equal \( 3 \cdot \lceil \alpha + 1 \rceil \). For \( n < N_0 \), set \( \mathcal{R}_{\alpha m} \) to be the sequence \( \langle n \rangle \), containing a single run of length \( n \). For \( n \geq N_0 \), define \( n''' = \lfloor \frac{n}{\alpha + 1} \rfloor + 1 \) and \( n^* = n - n''' \). Thus \( n''' \) is the least integer greater than \( n/(\alpha + 1) \). Similarly define \( n'' = \lfloor \frac{n^*}{\alpha + 1} \rfloor + 1 \) and \( n' = n^* - n'' \).

These four values can be equivalently uniquely characterized as satisfying

\[
\begin{align*}
n''' &= \frac{1}{\alpha + 1} n + \epsilon_1 \\
n'' &= \frac{\alpha}{(\alpha + 1)^2} n - \frac{1}{\alpha + 1} \epsilon_1 + \epsilon_2 \\
n^* &= \frac{n}{\alpha + 1} - \epsilon_1 \\
n' &= \frac{\alpha^2}{(\alpha + 1)^2} n - \frac{\alpha}{\alpha + 1} \epsilon_1 - \epsilon_2
\end{align*}
\]

for some \( \epsilon_1, \epsilon_2 \in (0, 1] \). The sequence \( \mathcal{R}_{\alpha m}(n) \) of run lengths is inductively defined to be the concatenation of \( \mathcal{R}_{\alpha m}(n') \), \( \mathcal{R}_{\alpha m}(n'') \) and \( \mathcal{R}_{\alpha m}(n''' \).

Claim 16. Let \( \alpha > 1 \) and \( n \geq N_0 \).

a. \( n = n' + n'' + n''' \) and \( n^* = n' + n'' \).

b. \( \alpha(n''' - 3) \leq n^* < \alpha n''' \).

c. \( \alpha(n'' - 3) \leq n' < \alpha n'' \).

d. \( n''' \geq 3 \).

e. \( n' \geq 1 \) and \( n'' \geq 1 \).
Part d. follows from (3) and ties (3) since 0 < \epsilon_1 \leq 1 and \alpha > 1. Part c. is similarly immediate from (4) since also 0 < \epsilon_2 \leq 1. Part d. follows from (3) and \( n \geq N_0 \geq 3(\alpha + 1) \). Part e. follows by (4), \alpha > 1, and \( n \geq N_0 \).

**Claim 17.** Let \( \alpha > 1 \) and \( R_{\kappa m}(n) \) be as defined above.

a. The sums of the run lengths in \( R_{\kappa m}(n) \) is \( n \).

b. If \( n \geq N_0 \), then the final run length in \( R_{\kappa m}(n) \) is \( \geq 3 \).

c. Suppose that \( R_{\kappa m}(n) \) is the initial subsequence of a sequence \( R' \) of run lengths and that the \( \alpha \)-merge sort is initially started with run lengths \( R' \) and (a) the stack \( \mathcal{X} \) empty or (b) with the top element of \( \mathcal{X} \) a run of length \( \geq \alpha(n - 3) \). Then the \( \alpha \)-merge sort will start by processing exactly the runs whose lengths are those of \( R_{\kappa m}(n) \), merging them into single run which becomes the new top element of \( \mathcal{X} \). This will be done without merging any runs that were initially in \( \mathcal{X} \) and without (yet) processing any of the remaining runs in \( R' \).

d. The property c. also holds for \( \alpha \)-stack sort.

Part a. is immediate from the definitions using induction on \( n \). Part b. is a consequence of Claim 16(d.) and the fact that the final entry of \( R_{\kappa m} \) is a value \( n''' < N_0 \) for some \( n \). Part c. is proved by induction on \( n \), similarly to the proof of Claim 5. It is trivial for the base case \( n < N_0 \). For \( n \geq N_0 \), \( R_{\kappa m}(n) \) is the concatenation of \( R_{\kappa m}(n') \), \( R_{\kappa m}(n'') \), \( R_{\kappa m}(n''') \). Applying the induction hypothesis to \( R_{\kappa m}(n') \) yields that these runs are initially merged into a single new run of length \( n' \) at the top of the stack. Then applying the induction hypothesis to \( R_{\kappa m}(n'') \) shows that those runs are merged to become the top run on the stack. Since the last member of \( R_{\kappa m}(n'') \) is a run of length \( \geq 3 \), every intermediate member placed on the stack while merging the runs of \( R_{\kappa m}(n'') \) has length \( \leq n''' - 3 \). And, by Claim 16(c.), these cannot cause a merge with the run of length \( n' \) already in \( \mathcal{X} \). Next, again by Claim 16(c.), the top two members of the stack are merged to form a run of length \( n^* = n' + n''' \). Applying the induction hypothesis a third time, and arguing similarly with Claim 16(b.), gives that the runs of \( R_{\kappa m}(n''') \) are merged into a single run of length \( n'''' \), and then merged with the run of length \( n^* \) to obtain a run of length \( n \). This proves part c. of Claim 17.

Part d. is proved exactly like part c.; the fact that \( \alpha \)-stack sort is only 2-aware and never merges \( X \) and \( Y \) makes the argument slightly easier in fact. This completes the proof of Claim 17.

**Claim 18.** Let \( \alpha > 1 \) be fixed, and let \( c(x) \) equal the merge cost of the \( \alpha \)-merge sort on an input sequence with run lengths given by \( R_{\kappa m}(n) \). Then \( c(n) = 0 \) for \( n < N_0 \). For \( n \geq N_0 \),

\[
c(n) = c(n') + c(n'') + c(n''') + 2n' + 2n'' + n'''.
\]  

Equation (5) is an immediate consequence of the proof of part c. of Claim 17. To see that \( c(n) \) is increasing for \( n \geq N_0 \), let \( (n+1)' \), \( (n+1)'' \), \( (n+1)''' \) indicate the three values such that \( R_{\kappa m}(n+1) \) is the concatenation of \( R_{\kappa m}((n+1)') \), \( R_{\kappa m}((n+1)'' \) and \( R_{\kappa m}((n+1)''' \). We use \( (n+1)' = (n+1) - (n+1)''' \). Then it is easy to check that either \( (n+1)''' = n''''+1 \) and \( (n+1)' = n^* \), or \( (n+1)' = n'' \) and \( (n+1)' = n^* + 1 \). And if \( (n+1)' = n^* + 1 \) then either \( (n+1)' = n''''+1 \) and \( (n+1)' = n^* + 1 \), or \( (n+1)' = n'' \) and \( (n+1)' = n^* + 1 \). In other words, \( (n+1)' \), \( (n+1)'' \), \( (n+1)''' \) differ from \( n', n'', n''' \) in that exactly one of them is increased by 1 and the other two are unchanged. Thus \( 2n' + 2n'' + n''' \) is a strictly increasing function of \( n \). An easy proof by induction now shows that \( c(n+1) > c(n) \) for \( n \geq N_0 \), and Claim 18 is proved.

Let \( \delta = [2(\alpha + 1)^2/(2\alpha^2 + 1)] \). (For \( 1 < \alpha \leq 2 \), we have \( \delta \leq 1 \). We have \( \delta \leq N_0 - 1 \) for all \( \alpha > 1 \). For real \( x \geq N_0 \), define \( b(x) = c([x] - \delta) \). Since \( c(n) \) is increasing, \( b(x) \) is nondecreasing.
Claim 19. a. \( \frac{1}{\alpha+1} n - \delta \leq (n-\delta)^{\prime\prime}. \)

b. \( \frac{\alpha^2}{(\alpha+1)^2} n - \delta \leq (n-\delta)^{\prime}. \)

c. \( \frac{\alpha^2}{(\alpha+1)^2} n - \delta \leq (n-\delta)^{\prime}. \)

d. For \( x \geq N_0 + \delta, \)
\[ b(x) \geq b\left(\frac{\alpha^2}{(\alpha+1)^2} x\right) + b\left(\frac{\alpha}{(\alpha+1)^2} x\right) + b\left(\frac{1}{\alpha+1} x\right) + \frac{2\alpha+1}{\alpha+1} (x-\delta-1). \tag{6} \]

For a., (3) implies that \( (n-\delta)^{\prime\prime} \geq \frac{n-\delta}{\alpha+1} \), so a. follows from \( -\delta \leq -\delta/(\alpha+1) \). This holds as \( \delta > 0 \) and \( \alpha > 1 \). For b., (4) implies that \( (n-\delta)^{\prime} \geq \frac{\alpha^2}{(\alpha+1)^2} (n-\delta) - \frac{1}{\alpha+1} \), so after simplification, b. follows from \( \delta \geq (\alpha+1)/(\alpha^2+\alpha+1) \); it is easy to verify that this holds by choice of \( \delta \). For c., (4) also implies that \( (n-\delta)^{\prime} \geq \frac{\alpha^2}{(\alpha+1)^2} (n-\delta) - 2 \), so after simplification, c. follows from \( \delta \geq 2(\alpha+1)^2/(2\alpha+1) \).

To prove part d., letting \( n = \lfloor x \rfloor \) and using parts a., b. and c., equations (3) and (4), and the fact that \( b(x) \) and \( c(n) \) are nondecreasing, we have

\[ b(x) = c(n-\delta) \]
\[ = c\left(\lfloor \frac{\alpha^2}{(\alpha+1)^2} n - \delta \rfloor - \delta + 1\right) + c\left(\lfloor \frac{\alpha}{(\alpha+1)^2} n - \delta \rfloor - \delta + 1\right) + c\left(\lfloor \frac{1}{\alpha+1} n - \delta \rfloor - \delta + 1\right) + \frac{2\alpha+1}{\alpha+1} (x-\delta-1) \]
\[ \geq b\left(\frac{\alpha^2}{(\alpha+1)^2} x\right) + b\left(\frac{\alpha}{(\alpha+1)^2} x\right) + b\left(\frac{1}{\alpha+1} x\right) + \frac{2\alpha+1}{\alpha+1} (x-\delta-1) \]
\[ \geq b\left(\frac{\alpha^2}{(\alpha+1)^2} x\right) + b\left(\frac{\alpha}{(\alpha+1)^2} x\right) + b\left(\frac{1}{\alpha+1} x\right) + \frac{2\alpha+1}{\alpha+1} (x-\delta-1). \]

Claim 19(d.) gives us the basic recurrence needed to lower bound \( b(x) \) and hence \( c(n) \).

Claim 20. Fix \( \alpha > 1 \). For all \( x \geq \delta + 1, \)
\[ b(x) \geq c_\alpha \cdot x \log x - B_\alpha x + A, \tag{7} \]

where \( A = \frac{2\alpha+1}{2\alpha+2} (\delta+1) \) and \( B = \frac{A}{\delta+1} + c_\alpha \log(N_0 + \delta+1). \)

The claim is proved by induction, namely we prove by induction on \( n \) that (7) holds for all \( x < n \). The base case is for \( x < N_0+\delta+1 \): in this case \( b(x) = 0 \), and the righthand side of (7) is \( \leq 0 \) by choice of \( B \). Thus (7) holds trivially. For the induction step, the bound (7) is known to hold for \( b\left(\frac{\alpha^2}{(\alpha+1)^2} x\right) \), \( b\left(\frac{\alpha}{(\alpha+1)^2} x\right) \), and \( b\left(\frac{1}{\alpha+1} x\right) \). So by (6),
\[ b(x) \geq c_\alpha \frac{\alpha^2}{(\alpha+1)^2} x \log \frac{\alpha^2}{(\alpha+1)^2} x - B_\alpha \frac{\alpha^2}{(\alpha+1)^2} x + \frac{2\alpha+1}{2\alpha+2} (\delta+1) \]
\[ + c_\alpha \frac{\alpha}{(\alpha+1)^2} x \log \frac{\alpha}{(\alpha+1)^2} x - B_\alpha \frac{\alpha}{(\alpha+1)^2} x + \frac{2\alpha+1}{2\alpha+2} (\delta+1) \]
\[ + c_\alpha \frac{1}{\alpha+1} x - B_\alpha \frac{1}{\alpha+1} x + \frac{2\alpha+1}{\alpha+1} (\delta+1) \]
\[ = c_\alpha x \log x - B_\alpha x + A \]
\[ + c_\alpha x \left[ \frac{\alpha^2}{(\alpha+1)^2} \log \frac{\alpha^2}{(\alpha+1)^2} + \frac{\alpha}{(\alpha+1)^2} \log \frac{\alpha}{(\alpha+1)^2} + \frac{1}{\alpha+1} \log \frac{1}{\alpha+1} \right] + \frac{2\alpha+1}{\alpha+1} x. \]
The quantity in square brackets is equal to
\[
\left( \frac{2\alpha^2}{(\alpha+1)^2} + \frac{\alpha}{(\alpha+1)^2} \right) \log \alpha - \left( \frac{2\alpha^2}{(\alpha+1)^2} + \frac{2\alpha}{(\alpha+1)^2} + \frac{1}{\alpha+1} \right) \log(\alpha+1)
\]
\[
= \frac{\alpha(\alpha+1)}{(\alpha+1)^2} \log \alpha - \frac{2\alpha^2 + 3\alpha + 1}{(\alpha+1)^2} \log(\alpha+1)
\]
\[
= \frac{\alpha(\alpha+1)}{(\alpha+1)^2} \log \alpha - \frac{2\alpha + 1}{\alpha+1} \log(\alpha+1)
\]
\[
= \frac{\alpha \log \alpha - (\alpha+1) \log(\alpha+1)}{\alpha+1} \cdot \frac{2\alpha + 1}{\alpha+1}.
\]
Since \(c_\alpha = (\alpha+1)/((\alpha+1) \log(\alpha+1) - \alpha \log \alpha)\), we get that \(b(x) \geq c_\alpha x \log x - Bx + A\). This completes the induction step and proves Claim 20.

Since \(A\) and \(B\) are constants, this gives \(b(x) \geq (c_\alpha - o(1)) x \log x\). Therefore \(c(n) = b(n+\delta) \geq (c_\alpha - o(1)) n \log n\). This completes the proofs of Theorems 8, 14 and 15.

\[ \Box \]

### 5.2 Upper bound for 2-merge sort and \(\alpha\)-merge sort — preliminaries

We next prove upper bounds on the worst-case runtime of the 2-merge sort and the \(\alpha\)-merge sort for \(\varphi < \alpha < 2\). The upper bounds will have the form \(n \cdot (d_\alpha + c_\alpha \log n)\), with no hidden or missing constants. \(c_\alpha\) was already defined in (2). For \(\alpha = 2\), \(c_2 \approx 1.08897\) and the constant \(d_2\) is
\[
d_2 = 6 - c_2 \cdot (3 \log 6 - 2 \log 4) = 6 - c_2 \cdot ((3 \log 3) - 1) \approx 1.91104. \tag{8}
\]
For \(\varphi < \alpha < 2\), first define
\[
k_0(\alpha) = \min\{\ell \in \mathbb{N} : \frac{\alpha^2 - \alpha - 1}{\alpha - 1} \geq \frac{1}{\alpha^\ell}\}. \tag{9}
\]
Note \(k_0(\alpha) \geq 1\). Then set, for \(\varphi < \alpha < 2\),
\[
d_\alpha = \frac{2^k_0(\alpha) + 1}{\alpha - 1} \cdot \max\{(k_0(\alpha) + 1), 3\} \cdot (2\alpha - 1) + 1. \tag{10}
\]
Our proof for \(\alpha = 2\) is substantially simpler than the proof for general \(\alpha\): it also gives the better constant \(d_2\). The limits \(\lim_{\alpha \to \varphi^+} k_0(\alpha)\) and \(\lim_{\alpha \to \varphi^+} d_\alpha\) are both equal to \(\infty\); we suspect this is not optimal.\(^4\) However, by Theorems 14 and 15, the constant \(c_\alpha\) is optimal.

**Theorem 21.** Let \(\varphi < \alpha < 2\). The merge cost of the \(\alpha\)-merge sort on inputs of length \(n\) composed of \(m\) runs is \(\leq n \cdot (d_\alpha + c_\alpha \log m)\).

The corresponding upper bound for \(\alpha = 2\) is:

**Theorem 22.** The merge cost of the 2-merge sort on inputs of length \(n\) composed of \(m\) runs is \(\leq n \cdot (d_2 + c_2 \log m) \approx n \cdot (1.91104 + 1.08897 \log m)\).

The proofs of these theorems will allow us to easily prove the following upper bound on the size of the stack:

**Theorem 23.** Let \(\varphi < \alpha < 2\). For \(\alpha\)-merge sort on inputs of length \(n\), the size \(|\mathcal{X}|\) of the stack is always \(< 3 + \log_\alpha n = 3 + (\log n)/(\log \alpha)\). For 2-merge sort: the size of the stack is always \(< 2 + \log n\).

\(^4\)Already the term \(2^{k_0(\alpha) + 1}\) is not optimal as the proof of Theorem 21 shows that the base 2 could be replaced by \(\sqrt{\alpha+1}\); we conjecture however, that in fact it is not necessary for the limit of \(d_\alpha\) to be infinite.
Lemma 25. Let \( \alpha > 1 \) and \( \alpha < 2 \). Let \( A, B, a, b \) be positive integers such that \( A \leq \alpha B \) and \( B \leq \alpha A \). Then
\[
\alpha \cdot c_\alpha \log a + B \cdot c_\alpha \log b + A + B \leq (A+B) \cdot c_\alpha \log(a+b).
\] (11)

Lemma 26. Let \( \alpha > 1 \) and \( A, B, a, b \) be positive integers.

(a) (For \( \alpha = 2 \)) If \( A \geq 2 \) and \( A < 2B \), then
\[
A \cdot (d_2 + c_2 \log(a-1)) + A + B \leq (A+B) \cdot (d_2 - 1 + c_2 \log(a+b)).
\]

(b) If \( \alpha < 2 \) and \( A \leq \frac{\alpha}{\alpha-1} \cdot B \), then
\[
A \cdot (d_\alpha + c_\alpha \log a) + A + B \leq (A+B) \cdot (d_\alpha - 1 + c_\alpha \log(a+b)).
\]

Lemma 27. Let \( \varphi < \alpha < 2 \). Let \( A, B, C, a, b, \) and \( k \) be positive integers such that \( k \leq k_0(\alpha) + 1 \) and \( \frac{2^k(2\alpha-1)}{\alpha-1} C \geq A + B + C \). Then
\[
A \cdot (d_\alpha + c_\alpha \log a) + B \cdot (d_\alpha + c_\alpha \log b)) + k \cdot C + 2B + A \leq A \cdot (d_\alpha - 1 + c_\alpha \log a) + (B + C) \cdot (d_\alpha - 1 + c_\alpha \log(b+1)).
\]

Proof of Lemma 24. The inequality (11) is equivalent to
\[
A \cdot (c_\alpha \log a - c_\alpha \log(a+b) + 1) \leq B \cdot (c_\alpha \log(a + b) - c_\alpha \log b - 1)
\]
and hence to
\[
A \cdot \left(1 + c_\alpha \log \frac{a}{a+b}\right) \leq B \cdot \left(-1 - c_\alpha \log \frac{b}{a+b}\right).
\]
Setting \( t = b/(a+b) \), this is the same as
\[
A \cdot (1 + c_\alpha \log(1-t)) \leq B \cdot (-1 - c_\alpha \log t).
\]
Let \( t_0 = 1 - 2^{-1/c_\alpha} \). Since \( c_\alpha > 1 \), we have \( t_0 < 1/2 \), so \( t_0 < 1-t_0 \). The lefthand side of (14) is positive iff \( t < t_0 \). Likewise, the righthand side is positive iff \( t < 1-t_0 \). Thus (14) certainly holds when \( t_0 \leq t \leq 1-t_0 \) where the lefthand side is \( \leq 0 \) and the righthand side is \( \geq 0 \).
Suppose \( 0 < t < t_0 \), so \( 1 + c_\alpha \log(1-t) \) and \(-1 - c_\alpha \log t\) are both positive. Since \( A \leq \alpha B \), to prove (14) it will suffice to prove \( \alpha(1 + c_\alpha \log(1-t)) \leq -1 - c_\alpha \log t \), or equivalently that 
\[-1 - \alpha \geq c_\alpha \log(t(1-t)^{\alpha}).\]

The derivative of \( \log(t(1-t)^{\alpha}) \) is \((1 - (1 + \alpha)t)/(t(1-t))\); so \( \log(t(1-t)^{\alpha}) \) is maximized at \( t = 1/(1+\alpha) \) with value \( \alpha \log \alpha - (\alpha+1) \log(\alpha+1) \). Thus the desired inequality holds by the definition of \( c_\alpha \), so (14) holds in this case.

Now suppose \( 1-t_0 < t < 1 \), so \( 1 + c_\alpha \log(1-t) \) and \(-1 - c_\alpha \log t\) are both negative. Since \( B \leq \alpha A \), it suffices to prove \( 1 + c_\alpha \log(1-t) \leq \alpha(-1 - c_\alpha \log t) \) or equivalently that \(-1 - \alpha \geq c_\alpha \log(t^\alpha(1-t))\).

This is identical to the situation of the previous paragraph, but with \( t \) replaced by \( 1-t \), so (14) holds in this case also.

**Proof of Lemma 25.** The inequality (12) is equivalent to
\[
B \cdot (1 + c_\alpha \log b - c_\alpha \log(a+b)) \leq A \cdot (c_\alpha \log(a+b) - c_\alpha \log a).
\]

Since \( \log(a+b) - \log a > 0 \) and \((\alpha-1)B \leq A\), it suffices to prove
\[
1 + c_\alpha \log b - c_\alpha \log(a+b) \leq (\alpha-1) \cdot (c_\alpha \log(a+b) - c_\alpha \log a).
\]

This is equivalent to
\[
c_\alpha \log b + (\alpha-1) \cdot c_\alpha \log(a) - \alpha \cdot c_\alpha \log(a+b) \leq -1.
\]

Letting \( t = b/(a+b) \), we must show \(-1 \geq c_\alpha \log(t(1-t)^{\alpha-1})\). Similarly to the previous proof, taking the first derivative shows that the righthand side is maximized with \( t = 1/\alpha \), so it will suffice to show that \(-1 \geq c_\alpha \log((\alpha-1)^{\alpha-1}/\alpha^\alpha)\), i.e., that \( c_\alpha \cdot (\alpha \log \alpha - (\alpha-1) \log(\alpha-1)) \geq 1 \). Numerical examination shows that this is true for \( \alpha > 1.29 \).

**Proof of Lemma 26.** We assume w.l.o.g. that \( b = 1 \). The inequality of part (a) is equivalent to
\[
A \cdot (2 + c_2 \log(a-1) - c_2 \log(a+1)) \leq B \cdot (d_2 - 2 + c_2 \log(a+1)).
\]

Since the righthand side is positive and \( A \leq 2B \), we need to prove
\[
2 \cdot (2 + c_2 \log(a-1) - c_2 \log(a+1)) \leq d_2 - 2 + c_2 \log(a+1).
\]

This is easily seen to be the same as \( 6 - d_2 \leq c_2 \log((a+1)^3/(a-1)^2) \). With \( a > 1 \) an integer, the quantity \((a+1)^3/(a-1)^2\) is minimized when \( a = 5 \). Thus, we must show that
\[
d_2 \geq 6 - c_2 \log(6^3/4^2) = 6 - c_2 (3 \log 6 - 2 \log 4).
\]

In fact, \( d_2 \) was defined so that equality holds. Thus (a) holds.

Arguing similarly for part (b), we must show
\[
\frac{2\alpha}{\alpha - 1} + 2 - d_\alpha \leq c_2 \log((a+1)^\alpha/(a-1)/a).
\]

This holds trivially, as \( d_\alpha \geq 12 \) for \( \alpha < 2 \) so the lefthand side is negative and the righthand side is positive.

**Proof of Lemma 27.** The inequality (13) is equivalent to
\[
2A + B \cdot (3 + c_\alpha \log b - c_\alpha \log(b+1)) + k \cdot C \leq C \cdot (d_\alpha - 1 + c_\alpha \log(b+1)).
\]

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Since \( \frac{2^k(2\alpha-1)}{\alpha-1} C \geq A + B + C \), it is enough to prove
\[
\max(k, 3) \cdot \frac{2^k(2\alpha-1)}{\alpha-1} C \leq (d_\alpha - 1) \cdot C.
\]
This is equivalent to
\[
d_\alpha \geq \frac{2^k \cdot \max\{ k, 3 \} \cdot (2\alpha-1)}{\alpha - 1} + 1.
\]
This holds by the definition of \( d_\alpha \), since \( k \leq k_0(\alpha)+1 \). \( \square \)

The proofs of Theorems 21 and 22 use two functions \( G_\alpha \) and \( H_\alpha \) to bound the merge cost of runs stored on the stack.

**Definition 28.** For \( \alpha = 2 \), define
\[
G_2(n, m) = n \cdot (d_2 - 1 + c_2 \log m)
\]
\[
H_2(n, m) = \begin{cases} n \cdot (d_2 + c_2 \log(m-1)) & \text{if } m \geq 2 \\ 0 & \text{if } m = 1. \end{cases}
\]

For \( \alpha < 2 \),
\[
G_\alpha(n, m) = n \cdot (d_\alpha - 1 + c_\alpha \log m)
\]
\[
H_\alpha(n, m) = n \cdot (d_\alpha + c_\alpha \log m).
\]

Recall that \( m_X \) is the number of original runs merged to form a run \( X \). For the proof of Theorem 22 in the next section, upper bounding the merge cost of the 2-merge sort, the idea is that for most runs \( X \) on the stack \( X \), the merge cost of \( X \) will be bounded by \( G_2(|X|, m_X) \). However, many of the runs formed by merges in cases (B) and (C) will instead have merge cost bounded by \( H_2(|X|, m_X) \).

A similar intuition applies to the proof of Theorem 21 for \( \varphi < \alpha < 2 \), in Section 5.4. However, the situation is more complicated as that proof will bound the total merge cost instead of individual merge costs \( w_{X_i} \).

The next lemma is the crucial property of \( G_2 \) and \( G_\alpha \) which needed for both Theorems 22 and 21. The lemma is used to bound the merge costs incurred when merging two runs which differ in size by at most a factor \( \alpha \). The constant \( c_\alpha \) is exactly what is needed to make this lemma hold.

**Lemma 29.** Suppose \( n_1, n_2, m_1, m_2 \) are positive integers, and \( \varphi < \alpha \leq 2 \). Also suppose \( n_1 \leq \alpha n_2 \) and \( n_2 \leq \alpha n_1 \). Then,
\[
G_\alpha(n_1, m_1) + G_\alpha(n_2, m_2) + n_1 + n_2 \leq G_\alpha(n_1+n_2, m_1+m_2).
\]

**Proof.** The inequality expresses that
\[
n_1 \cdot (d_\alpha - 1 + c_\alpha \log m_1) + n_2 \cdot (d_\alpha - 1 + c_\alpha \log m_2) + n_1 + n_2 \leq (n_1 + n_2) \cdot (d_\alpha - 1 + c_\alpha \log(m_1+m_2)).
\]
This is an immediate consequence of Lemma 24 with \( A, B, a, b \) replaced with \( n_1, n_2, m_1, m_2 \). \( \square \)
5.3 Upper bound proof for 2-merge sort

This section gives the proof of Theorem 22. The next lemma states some properties of $G_2$ and $H_2$ which follow from Lemmas 25 and 26(a).

Lemma 30. Suppose $n_1, n_2, m_1, m_2$ are positive integers.

(a) If $n_2 \leq n_1$, then

$$G_2(n_1, m_1) + H_2(n_2, m_2) + n_1 + n_2 \leq H_2(n_1+n_2, m_1+m_2).$$

(b) If $n_1 \leq 2n_2$, then

$$H_2(n_1, m_1) + n_1 + n_2 \leq G_2(n_1+n_2, m_1+m_2).$$

Proof. If $m_2 \geq 2$, part (a) states that

$$n_1 \cdot (d_2 - 1 + c_2 \log m_1) + n_2 \cdot (d_2 + c_2 \log(m_2-1)) + n_1 + n_2 \leq (n_1+n_2) \cdot (d_2 + c_2 \log(m_2+m_2-1)).$$

This is an immediate consequence of Lemma 25. If $m_2 = 1$, then part (a) states

$$n_1 \cdot (d_2 - 1 + c_2 \log m_1) + n_1 + n_2 \leq (n_1+n_2) \cdot (d_2 + c_2 \log m_1).$$

This holds since $d_2 \geq 1$ and $n_2 > 0$ and $m_1 \geq 1$.

When $m_1 \geq 2$, part (b) states that

$$n_1 \cdot (d_2 + c_2 \log(m_1-1)) + n_1 + n_2 \leq (n_1+n_2) \cdot (d_2 - 1 + c_2 \log(m_1+m_2));$$

this is exactly Lemma 26(a). When $m_1 = 1$, (b) states $n_1+n_2 \leq (n_1+n_2)((d_2-1)+c_2 \log(m_2+1))$, and this is trivial since $c_2 + d_2 \geq 2$ and $m_2 \geq 1$.

We next prove Theorem 22. We use the convention that the 2-merge sort maintains a stack $X$ containing runs $X_1, X_2, \ldots, X_\ell$. The last four runs are denoted $W, X, Y, Z$. Each $X_i$ is a run of $|X_i|$ many elements. We write $m_{X_i}$ and $w_{X_i}$ to denote the number of original runs that were merged to form $X_i$ and the merge cost of $X_i$ (respectively). If $X_i$ is an original run, then $m_{X_i} = 1$ and $w_{X_i} = 0$. If $m_{X_i} = 2$, then $X_i$ was formed by a single merge, so $w_{X_i} = |X_i|$. To avoid handling the special cases for $\ell \leq 2$, we adopt the convention that there is a virtual initial run $X_0$ with infinite length, so $|X_0| = \infty$.

Lemma 31. Suppose $X_i$ is a run in $X$ and that $w_{X_i} \leq G_2(|X_i|, m_{X_i})$, then $w_{X_i} \leq H_2(|X_i|, m_{X_i})$.

Proof. If $m_{X_i} = 1$, then the lemma holds since $w_X = 0$. If $m_{X_i} = 2$, then it holds since $w_{X_i} = |X_i|$. If $m_{X_i} > 2$, then it holds since $c_2 \log(m_{X_i}/(m_{X_i}-1)) < 1$ and hence $G_2(|X_i|, m_{X_i}) < H_2(|X_i|, m_{X_i})$.

Proof of Theorem 22. We describe the 2-merge algorithm by using three invariants (A), (B), (C) for the stack; and analyzing what action is taken in each situation. Initially, the stack contains a single original $X_1$, so $\ell = 1$ and $m_{X_1} = 1$ and $w_{X_1} = 0$, and case (A) applies.

(A): Normal mode. The stack satisfies

(A-1) $|X_i| \geq 2 \cdot |X_{i+1}|$ for all $i < \ell - 1$. This includes $|X| \geq 2|Y|$ if $\ell \geq 2$.

(A-2) $2 \cdot |Y| \geq |Z|$; i.e. $2|X_{\ell-1}| \geq |X_\ell|$.

(A-3) $w_{X_i} \leq G_2(|X_i|, m_{X_i})$ for all $i \leq \ell$. 

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If $\ell \geq 2$, (A-1) and (A-2) imply $|X| \geq |Z|$, i.e. $|X_{\ell-2}| \geq |X_{\ell}|$. The $\alpha$-merge algorithm does one of the following:

- If $2|Z| \leq |Y|$ and there are no more original runs to load, then it goes to case (B). We claim the four conditions of (B) hold (see below). The condition (B-2) holds by (A-2), and (B-1) and (B-3) hold by (A-1) and (A-3). Condition (B-4) holds by (A-3) and Lemma 31.

- If $2|Z| \leq |Y|$ and there is another original run to load, then the algorithm loads the next run as $X_{\ell+1}$.
  - If $|X_{\ell+1}| \leq 2|X_{\ell}|$, then we claim that case (A) still holds with $\ell$ incremented by one. In particular, (A-1) will hold $|Y| \geq 2|Z|$ is the same as $2|X_{\ell}| \leq |X_{\ell-1}|$. Condition (A-2) will hold by the assumed bound on $|X_{\ell+1}|$. Condition (A-3) will still hold since $|X_{\ell+1}|$ is an original run so $m_{X_{\ell+1}} = 1$ and $w_{X_{\ell+1}} = 0$.
  - Otherwise $|X_{\ell+1}| > 2|X_{\ell}|$, and we claim that case (C) below holds with $\ell$ incremented by one. (C-1) and (C-4) will hold by (A-1) and (A-3). For (C-2), we need $|X_{\ell-1}| \geq |X_{\ell}|$; i.e. $|Y| \geq |Z|$: this follows trivially from $|Y| \geq 2|Z|$. (C-5) holds by (A-3) and Lemma 31. (C-3) holds since $2|X_{\ell}| < |X_{\ell+1}|$. (C-6) holds since $X_{\ell+1}$ is an original run.

- If $2|Z| > |Y|$, then the algorithm merges the two runs $Y$ and $Z$. We claim the resulting stack satisfies condition (A) with $\ell$ decremented by one. (A-1) clearly will still hold. For (A-2) to still hold, we need $2|X| \geq |Y|+|Z|$: this follows from $2|Y| \leq |X|$ and $|Z| \leq |X|$. (A-3) will clearly still hold for all $i < \ell-1$. For $i = \ell-1$, since merging $Y$ and $Z$ added $|Y|+|Z|$ to the merge cost, (A-3) implies that the new top stack element will have merge cost at most

$$G_2(|Y|, m_Y) + G_2(|Z|, m_Z) + |Y| + |Z|.$$

By (A-2) and and Lemma 29, this is $\leq G_2(|Y|+|Z|, m_Y+m_Z)$, so (A-3) holds.

(B): Wrapup mode, lines 15-18 of Algorithm 6. There are no more original runs to process. The entire input has been combined into the runs $X_1, \ldots, X_\ell$ and they satisfy:

<table>
<thead>
<tr>
<th>Condition</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B-1</td>
<td>$</td>
</tr>
<tr>
<td>B-2</td>
<td>$</td>
</tr>
<tr>
<td>B-3</td>
<td>$w_{X_i} \leq G_2(</td>
</tr>
<tr>
<td>B-4</td>
<td>$w_Z \leq H_2(</td>
</tr>
</tbody>
</table>

If $\ell = 1$, the run $Z = X_1$ contains the entire input in sorted order and the algorithm terminates. The total merge cost is $\leq H_2(|Z|, m_Z)$. This is $< n \cdot (d_2 + c_2 \log m)$ as needed for Theorem 22.

Otherwise $\ell > 1$, and $Y$ and $Z$ are merged. We claim the resulting stack of runs satisfies case (B), now with $\ell$ decremented by one. It is obvious that (B-1) and (B-3) still hold. (B-4) will still hold since by (B-3) and (B-4) the merge cost of the run formed by merging $Y$ and $Z$ is at most $|Y| + |Z| + G_2(|Y|, m_Y) + H_2(|Z|, m_Z)$, and this is $\leq H_2(|Y|+|Z|, m_Y+m_Z)$ by Lemma 30(a).

To show (B-2) still holds, we must show that $|X| \geq |Y|+|Z|$. To prove this, note that $\frac{1}{2}|X| \geq |Y|$ by (B-1); thus from (B-2), also $\frac{1}{2}|X| \geq |Z|$. Hence $|X| \geq |Y|+|Z|$.

(C): Encountered long run $Z$. When case (C) is first entered, the final run $|Z|$ is long relative to $|Y|$. The algorithm will repeatedly merge $X$ and $Y$ until $|Z| \leq |X|$, at which point it merges $Y$ and $Z$ and returns to case (A). (The merge of $Y$ and $Z$ must eventually occur by the convention that $X_0$ has infinite length.) The following conditions hold with $\ell \geq 2$:

---

Note that in this case, if $\ell \geq 2$, $|Z| < |X|$, since (B-1) and (B-2) imply $|X| \geq 2|Y| \geq 2|Z| > |Z|$. This is the reason why Algorithm 5 does not check for the condition $|X| < |Z|$ in lines 14-16 (unlike what is done on line 7).
Theorem 22; however, we must handle a new, and fairly difficult, case (D). It is also necessary
this section gives the proof Theorem 21. The general outline of the proof is similar to that of
Theorem 22; however, we must handle a new, and fairly difficult, case (D). It is also necessary
to show that\( W \geq |X| \) and Lemma 30(b) this is\( \leq H_2(|Y|, m_Y) \). Hence\( W \geq |X|+|Y| \). To establish that (C-3) still holds, we must prove that
\( |X|+|Y| < 2|Z| \). By the assumption that \( |Z| > |X| \), this follows from\( |Y| \leq |X| \), which holds
by (C-2).

\begin{itemize}
  \item Suppose \( |Z| > |X| \). Then \( \ell \geq 3 \) and the algorithm merges \( X \) and \( Y \). We claim that case (C)
still holds, now with \( \ell \) decremented by 1. It is obvious that (C-1), (C-4) and (C-6) still hold.
(C-5) will still hold, since by (C-4) and (C-5), the merge cost of the run obtained by merging \( X \)
and \( Y \) is at most \( |X|+|Y|+G_2(|X|, m_X)+H_2(|Y|, m_Y) \), and this is \( \leq H_2(|X|+|Y|, m_X+m_Y) \)
by Lemma 30(a) since \( |X| \geq |Y| \). To see that (C-2) still holds, we argue exactly as in case (B)
to show that \( W \geq |X|+|Y| \). To prove this, note that \( \frac{1}{2}W \geq |X| \) by (C-1); thus from (C-2),
\( \frac{1}{2}W \geq |X|+|Y| \). Hence \( W \geq |X|+|Y| \). To establish that (C-3) still holds, we must prove that
\( |X|+|Y| < 2|Z| \). By the assumption that \( |Z| > |X| \), this follows from\( |Y| \leq |X| \), which holds
by (C-2).

\begin{itemize}
  \item Otherwise, \( |Z| \leq |X| \) and \( X \) and \( Y \) are merged. We claim that now case (A) will hold. (A-1)
will hold by (C-1). To show (A-2) will hold, we need \( |Y|+|Z| \leq 2|X| \): this holds by (C-2)
and \( |Z| \leq |X| \). (A-3) will hold for \( i < \ell-1 \) by (C-4). For \( i = \ell-1 \), the merge cost \( w_{YZ} \)
of the run obtained by merging \( Y \) and \( Z \) is \( \leq H_2(|Y|, m_Y)+|Y|+|Z| \) by (C-5) and (C-6). By (C-3)
and Lemma 30(b) this is \( \leq G_2(|Y|+|Z|, m_Y+m_Z) \). Hence (A-3) will hold with \( i = \ell-1 \).

That completes the proof of Theorem 22.
\end{itemize}

Examination of the above proof shows why the 2-merge Algorithm 5 does not need to test
the condition \( |X| < 2|Y| \) on line 6; in contrast to what the \( \alpha \)-merge Algorithm 6 does. In cases
(A) and (B), the test will fail by conditions (A-1) and (B-1). In case (C), condition (C-3) gives
\( |Y| < 2|Z| \), so an additional test would be redundant.

5.4 Upper bound proof for \( \alpha \)-merge sort

This section gives the proof Theorem 21. The general outline of the proof is similar to that of
Theorem 22; however, we must handle a new, and fairly difficult, case (D). It is also necessary
to bound the total merge cost \( \sum w_X \) of all the runs in the stack \( X \), instead of bounding each
individual merge cost \( w_X \). We first prove a lemma listing properties of \( G_\alpha \) and \( H_\alpha \) which follow
from Lemmas 25, 26(b) and 27. Parts (a) and (b) of the lemma generalize Lemma 30.

**Lemma 32.** Suppose \( n_1, n_2, m_1, m_2 \) are positive integers, and \( \varphi < \alpha < 2 \).

\begin{itemize}
  \item If \( (\alpha-1)n_2 \leq n_1 \), then
    \[ G_\alpha(n_1, m_1) + H_\alpha(n_2, m_2) + n_1 + n_2 \leq H_\alpha(n_1+n_2, m_1+m_2). \]

  \item If \( n_1 \leq \frac{\alpha}{\alpha-1} \cdot n_2 \), then
    \[ H_\alpha(n_1, m_1) + n_1 + n_2 \leq G_\alpha(n_1+n_2, m_1+m_2). \]
\end{itemize}
(c) If $n_1 \leq \frac{\alpha}{\alpha-1}n_2$, then
\[ H_\alpha(n_1, m_1) \leq G_\alpha(n_1, m_1) + G_\alpha(n_2, 1). \]

(d) If $k \leq k_0(\alpha)+1$ and $\frac{2k(2\alpha-1)}{\alpha-1}n_3 \geq n_1 + n_2 + n_3$, then
\[ H_\alpha(n_1, m_1) + H_\alpha(n_2, m_2) + k \cdot n_3 + n_1 + 2n_2 \leq G_\alpha(n_1+n_2+n_3, m_1+m_2+1). \]

Proof. Part (a) states that
\[ n_1 \cdot (d_\alpha - 1 + c_\alpha \log m_1) + n_2 \cdot (d_\alpha + c_\alpha \log m_2) + n_1 + n_2 \leq (n_1+n_2) \cdot (d_\alpha + c_\alpha \log(m_1+m_2)). \]

This is an immediate consequence of Lemma 25.

Part (b) states that
\[ n_1 \cdot (d_\alpha + c_\alpha \log m_1) + n_1 + n_2 \leq (n_1 + n_2) \cdot (d_\alpha - 1 + c_\alpha \log(m_1+m_2)). \]

This is exactly Lemma 26(b).

The inequality of part (c) states
\[ n_1 \cdot (d_\alpha + c_\alpha \log m_1) \leq n_1 \cdot (d_\alpha - 1 + c_\alpha \log m_1) + n_2 \cdot (d_\alpha - 1 + 0). \]

After cancelling common terms, this is the same as $n_1 \leq n_2 \cdot (d_\alpha-1)$. To establish this, it suffices to show that $d_\alpha-1 \geq \frac{\alpha}{\alpha-1}$. Since $k_0(\alpha) \geq 1$, we have $d_\alpha \geq \frac{12(2\alpha-1)}{\alpha-1} + 1$. And, since $\alpha > 1$, we have $12(2\alpha-1) > \alpha$. Therefore $d_\alpha-1 \geq \frac{\alpha}{\alpha-1}$, and (c) is proved.

Part (d) states that
\[
\begin{align*}
n_1 \cdot (d_\alpha + c_\alpha \log m_1) + n_2 \cdot (d_\alpha + c_\alpha \log m_2) + k \cdot n_3 + n_1 + 2n_2 \\
\leq (n_1 + n_2 + n_3) \cdot (d_\alpha - 1 + c_\alpha \log(m_1+m_2+1)).
\end{align*}
\]

Lemma 27 implies that
\[
\begin{align*}
n_1 \cdot (d_\alpha + c_\alpha \log m_1) + n_2 \cdot (d_\alpha + c_\alpha \log m_2) + k \cdot n_3 + n_1 + 2n_2 \\
\leq n_1 \cdot (d_\alpha - 1 + c_\alpha \log m_1) + (n_2 + n_3) \cdot (d_\alpha - 1 + c_\alpha \log(m_2+1)).
\end{align*}
\]

The desired inequality (15) follows easily.

We now prove Theorem 21.

Proof of Theorem 21. We describe the $\alpha$-merge algorithm using four invariants (A), (B), (C), (D) for the stack; and analyze what action is taken in each situation. Initially, the stack contains a single original $X_1$, so $\ell = 1$ and $m_{X_1} = 1$ and $w_{X_1} = 0$, and case (A) applies.

(A): Normal mode. The stack satisfies

(A-1) $|X_i| \geq \alpha |X_{i+1}|$ for all $i < \ell-1$. This includes $|X| \geq \alpha |Y|$ if $\ell \geq 2$.

(A-2) $\alpha |Y| \geq |Z|$; i.e. $\alpha |X_{\ell-1}| \geq |X_\ell|$.

(A-3) $\sum_{i=1}^{\ell} w_{X_i} \leq \sum_{i=1}^{\ell} G_\alpha(|X_i|, m_{X_i})$.

If $\ell \geq 2$, (A-1) and (A-2) imply $|X| \geq |Z|$, i.e. $|X_{\ell-2}| \geq |X_\ell|$. The $\alpha$-merge algorithm does one of the following:
• If $|α|Z| \leq |Y|$ and there are no more original runs to load, then it goes to case (B). Condition (B-1) holds by (A-1). (B-3) holds by (A-3) since $G_α(|X_ℓ|, m_{X_ℓ}) \leq H_α(|X_ℓ|, m_{X_ℓ})$. Condition (B-2) states that $(α - 1)|Z| \leq |Y|$ and this holds since $|Z| \leq |Y|$. 

• If $|α|Z| \leq |Y|$ and there is another original run to load, then the algorithm loads the next run as $X_{ℓ+1}$.
  
  - If $|X_{ℓ+1}| \leq |α|X_ℓ|$, then we claim that case (A) still holds after $ℓ$ is incremented by one. In particular, (A-1) and (A-2) imply that (A-1) will still hold since $|α|Z| \leq |Y|$ is the same as $|α|X_ℓ| \leq |X_{ℓ-1}|$. (A-2) still holds by the assumed bound on $|X_{ℓ+1}|$. Condition (A-3) still holds since $|X_{ℓ+1}|$ is an original run so $m_{X_{ℓ+1}} = 1$ and $w_{X_{ℓ+1}} = 0$.
  
  - Otherwise $|X_{ℓ+1}| > |α|X_ℓ|$, and we claim that case (C) below holds with $ℓ$ incremented by one. (C-1) holds by (A-1). For (C-2), we need $|X_{ℓ-1}| \geq (α-1)|X_ℓ|$, i.e. $|Y| \geq (α-1)|Z|$: this follows trivially from $|Y| \geq |α|Z|$. (C-4) holds by (A-3), since $G_α(|X_ℓ|, m_{X_ℓ}) \leq H_α(|X_ℓ|, m_{X_ℓ})$ and since $X_{ℓ+1}$ is an original run so $m_{X_{ℓ+1}} = 1$ and $w_{X_{ℓ+1}} = 0$. To have (C-3) hold, we need $|Z| \leq \frac{α}{(α-1)}|X_{ℓ+1}|$. This follows from the hypothesis $|X_{ℓ+1}| > |α|Z|$ and $α > 1$. Finally, (C-5) will hold since $X_{ℓ+1}$ is an original run.

• If $|α|Z| > |Y|$, then $ℓ \geq 2$. In this case, since $|Z| \leq |X|$, the algorithm merges the two runs $Y$ and $Z$. We claim the resulting stack satisfies case (A) with $ℓ$ decremented by one. It is obvious that (A-1) still holds. (A-3) holds by Lemma 29. For (A-2), we need $|Y| + |Z| \leq |α|X|$: this follows from $|Y| \leq \frac{1}{α}|X|$ and $|Z| \leq |X|$ and $1 + \frac{1}{α} < α$ as $φ < α$.

(B): Wrapup mode, lines 15-18 of Algorithm 6. There are no more original runs to process. The entire input has been combined into the runs $X_1, \ldots, X_ℓ$ and they satisfy:

(B-1) $|X_i| \geq |α|X_{i+1}|$ for all $i < ℓ-1$. This includes $|X| \geq |α|Y|$ if $ℓ \geq 2$.

(B-2) $|Y| \geq (α-1)|Z|$; i.e., $|X_{ℓ-1}| \geq (α-1)|X_ℓ|$.

(B-3) $\sum_{i=1}^{ℓ} w_{X_i} \leq \sum_{i=1}^{ℓ-1} G_α(|X_i|, m_{X_i}) + H_α(|X_ℓ|, m_{X_ℓ})$.

If $ℓ = 1$, the run $Z = X_1$ contains the entire input in sorted order and the algorithm terminates. The total merge cost is $\leq H_α(|Z|, m_Z)$. This is $n \cdot (d_α + c_α \log m)$ as needed for Theorem 21.

If $ℓ > 1$, then $Y$ and $Z$ are merged. We claim that the resulting stack of runs satisfies (B), now with $ℓ$ decremented by one. It is obvious that (B-1) will still holds. (B-3) will still hold since merging $Y$ and $Z$ adds $|Y| + |Z|$ to the total merge cost and since

$$G(|Y|, m_Y) + H(|Z|, m_Z) + |Y| + |Z| \leq H(|Y| + |Z|, m_Y + m_Z)$$

by Lemma 32(a) since $|Y| \geq (α-1)|Z|$ by (B-2). To show (B-2) will still hold, we must show that $|X| \geq (α-1)(|Y| + |Z|)$. To prove this, note that $\frac{1}{α}|X| \geq |Y|$ by (B-1); thus from (B-2), $\frac{1}{α(α-1)}|X| \geq |Z|$. This gives $\left(\frac{1}{α} + \frac{1}{α(α-1)}\right)|X| \geq |Y| + |Z|$; since $α > φ$, this implies $|X| \geq (α-1)(|Y| + |Z|)$.

(C): Encountered long run $Z$. When case (C) is first entered, the final run $Z$ is long relative to $Y$. The algorithm will repeatedly merge $X$ and $Y$ as long as $|Z| < |X|$, staying in case (C). Once $|Z| \leq |X|$, as discussed below, there are several possibilities. First, it may be that case (A) already applies. Otherwise, $Y$ and $Z$ are merged, and the algorithm proceeds to either case (A) or case (D).

Formally, the following conditions hold during case (C) with $ℓ \geq 2$:

\[\text{Note that in this case, if } ℓ \geq 2, |Z| < |X| \text{ since (B-1) and (B-2) imply that } |X| \geq |α|Y| \geq α(α-1)|Z| \text{ and } α^2 - α > 1 \text{ since } φ < α. \text{ This is the reason why Algorithm 6 does not check for the condition } |X| < |Z| \text{ in lines 14-16 (unlike what is done on line 7).}\]
(C-1) \( |X_i| \geq \alpha |X_{i+1}| \) for all \( i < \ell - 2 \). If \( \ell \geq 4 \), this includes \( |W| \geq \alpha |X| \).

(C-2) \( |X| \geq (\alpha - 1)|Y| \); i.e., \( |X_{\ell-2}| \geq (\alpha - 1)|X_{\ell-1}| \).

(C-3) \( |Y| \leq \frac{\alpha}{|\alpha - 1|} |Z| \); i.e., \( |X_{\ell-1}| \leq \frac{\alpha}{|\alpha - 1|} |X_{\ell}| \).

(C-4) \( \sum_{i=1}^{\ell} w_X \leq \sum_{i=1}^{\ell-2} G_a(|X_i|, m_{X_i}) + H_a(|Y|, m_Y) \).

(C-5) \( Z \) is an original run, so \( m_Z = 1 \) and \( w_Z = 0 \).

It is possible that no merge is needed, namely if \( |X| \geq \alpha |Y| \) and \( |Y| \geq \alpha |Z| \). In this case we claim that case (A) holds. Indeed, (A-1) will hold by (C-1) and since \( |X| \geq \alpha |Y| \). Condition (A-2) holds by \( |Y| \geq \alpha |Z| \). Condition (A-3) follows from (C-4) and the fact that, using (C-3), Lemma 32(c) gives the inequality \( H_a(|Y|, m_Y) \leq G_a(|Y|, m_Y) + G_a(|Z|, 1) \).

Otherwise, a merge occurs. The cases \( |Z| > |X| \) and \( |Z| \leq |X| \) are handled separately:

- Suppose \( |Z| > |X| \). We have \( \ell \geq 3 \) by the convention that \( |X_0| = \infty \), and the algorithm merges \( X \) and \( Y \). We claim that case (C) still holds, now with \( \ell \) decremented by 1. It is obvious that (C-1) and (C-5) will still hold. (C-4) will still hold since merging \( X \) and \( Y \) adds \( |X| + |Y| \) to the total merge cost, and since

\[
G_a(|X|, m_X) + H_a(|Y|, m_Y) + |X| + |Y| \leq H_a(|X| + |Y|, m_X + m_Y)
\]

by Lemma 32(a) since \( |X| \geq (\alpha - 1)|Y| \) by (C-3).

To see that (C-2) still holds, we argue exactly as in case (B): We must show that \( |W| \geq (\alpha - 1)(|X| + |Y|) \). To prove this, note that \( \frac{1}{\alpha} |W| \geq |X| \) by (C-1); thus from (C-2), \( \frac{1}{\alpha (\alpha - 1)} |W| \geq |Y| \). This gives \( \left( \frac{1}{\alpha} + \frac{1}{\alpha (\alpha - 1)} \right) |W| \geq |X| + |Y| \); hence \( |W| \geq (\alpha - 1)(|X| + |Y|) \).

To establish that (C-3) still holds, we must prove that \( |X| + |Y| \leq \frac{\alpha}{\alpha - 1} |Z| \). Since \( |Z| > |X| \), it suffices to show \( |X| + |Y| \leq \frac{\alpha}{\alpha - 1} |X| \). By (C-2), \( |Y| \leq \frac{\alpha}{\alpha - 1} |X| \), so \( |X| + |Y| \leq \left( 1 + \frac{1}{\alpha - 1} \right) |X| \), and so (C-3) will still hold.

- Otherwise \( |Z| \leq |X| \), so \( \ell \geq 2 \), and \( Y \) and \( Z \) are merged. The analysis splits into two cases, depending on whether \( |Y| + |Z| \leq \alpha |X| \) holds.

First, suppose \( |Y| + |Z| \leq \alpha |X| \). Then we claim that, after the merge of \( Y \) and \( Z \), case (A) holds. Indeed, (A-1) will hold by (C-1). (A-2) will hold by \( |Y| + |Z| \leq \alpha |X| \). Condition (A-3) will hold by (C-4) and (C-5) and the fact that, using (C-3), Lemma 32(b) gives the inequality \( H_a(|Y|, m_Y) + |Y| + |Z| \leq G_a(|Y| + |Z|, m_Y + 1) \).

Second, suppose \( |Y| + |Z| > \alpha |X| \) and thus \( \ell \geq 3 \). We claim that, after the merge of \( Y \) and \( Z \), case (D) holds. (D-1) holds by (C-1). (D-2) holds with \( k = 0 \) so \( Z_1 \) is the empty run, and with \( Z_2 \) and \( Z_3 \) equal to the just-merged runs \( Y \) and \( Z \) (respectively). (D-3) holds since \( k = 0 \) and \( |X| \geq |Z| \). (D-4) holds by (C-2) and the choice of \( Z_1 \) and \( Z_2 \). (D-5) holds by (C-3). (D-6) holds since \( \ell \) is the same as the assumption that \( |Y| + |Z| > \alpha |X| \). (D-7) holds since, by (C-3), \( |Y| + |Z| \leq \left( \frac{\alpha}{\alpha - 1} + 1 \right) |Z| = \frac{2\alpha - 1}{\alpha - 1} |Z| \). Finally, we claim that (D-8) holds by (C-4). To see this, note that with \( k = 0 \), the quantity \( (k+1)Z_3 + Z_2 \) of (D-8) is equal to the cost \( |Y| + |Z| \) of merging \( Y \) and \( Z \), and that the quantities \( m_Z - 1 \) and \( |Z_1| + |Z_2| \) of (D-8) are the same as our \( m_Y \) and \( |Y| \).

\footnote{It is this step which requires us to bound the total merge cost \( \sum_{i=1}^{w_X} w_{X_i} \) instead of the individual merge costs \( w_{X_i} \). Specifically, \( G_a(|Y|, m_Y) \) may not be an upper bound for \( w_Y \).}
**Case (D): Wrapping up handling a long run.** In case (D), the original long run, which was earlier called “Z” during case (C), is now called “Z₂” and has been merged with runs at the top of the stack to form the current top stack element Z. This Z is equal to the merge of three runs Z₁, Z₂ and Z₃. The runs Z₂ and Z₃ are the two runs Y and Z which were merged when leaving case (C) to enter case (D). The run Z₁ is equal to the merge of k many runs U₁, . . . , Uₖ which were just below the top of the stack when leaving case (C) to enter case (D). Initially k = 0, so Z₁ is empty.

The runs Z₂ and Z₃ do not change while the algorithm is in case (D). Since Z₃ was an original run, mZ₃ = 1. In other words, mZ₁ = mZ₂ + mZ₃.

There are two possibilities for how the merge algorithm proceeds in case (D). In the simpler case, it merges Y and Z, and either goes to case (A) or stays in case (D). If it stays in case (D), k is incremented by 1. In the more complicated case, it merges X and Y, then merges the resulting run with Z, and then again either goes to (A) or stays in (D). In this case, if it stays in (D), k is incremented by 2. Thus k is equal to the number of merges that have been performed. We will show that k < k₀(α) must always hold.

Formally, there is an integer k < k₀(α) and there exists runs Z₁, Z₂ and Z₃ (possibly Z₁ is empty) such that \( \ell \geq 2 \) and the following hold:

\[
\begin{align*}
&\text{(D-1)} \quad |X_i| \geq \alpha|X_{i+1}| \text{ for all } i < \ell - 1. \text{ This includes } X \geq \alpha Y. \\
&\text{(D-2)} \quad Z \text{ is equal to the merge of three runs } Z₁, Z₂, Z₃. \\
&\text{(D-3)} \quad |Y| \geq \alpha^k|Z₃|. \\
&\text{(D-4)} \quad |Y| \geq (\alpha-1)(|Z₁| + |Z₂|). \\
&\text{(D-5)} \quad |Z₃| \geq \frac{\alpha-1}{\alpha}|Z₂|. \\
&\text{(D-6)} \quad \alpha|Y| < |Z|. \\
&\text{(D-7)} \quad |Z| \leq \frac{2^k(2\alpha-1)}{\alpha-1}|Z₃|. \\
&\text{(D-8)} \quad \sum_{i=1}^{\ell} w_{X_i} \leq \sum_{i=1}^{\ell - 1} G_α(|X_i|, m_{X_i}) + (k+1)|Z₃| + |Z₂| + H_α(|Z₁| + |Z₂|, m_{Z₁} - 1).
\end{align*}
\]

We claim that conditions (D-3), (D-4) and (D-6) imply that k < k₀(α). To prove this, suppose k ≥ k₀(α). From the definition of k₀, this implies that \( \alpha \geq \frac{1}{\alpha^k} + \frac{1}{\alpha - 1} \). (D-3) gives \( \frac{1}{\alpha^k}|Y| \geq |Z₃| \); (D-4) gives \( \frac{1}{\alpha - 1}|Y| \geq |Z₁| + |Z₂| \). With (D-6) and \( |Z| = |Z₁| + |Z₂| + |Z₃| \), these imply

\[
|Z| > \alpha|Y| \geq \left( \frac{1}{\alpha^k} + \frac{1}{\alpha - 1} \right)|Y| \geq |Z₁| + |Z₂| + |Z₃| = |Z|,
\]

which is a contradiction.

By (D-6) and the test in line 6 of Algorithm 6, the algorithm must perform a merge, either of X and Y or of Y and Z, depending on the relative sizes of X and Z. The cases of \( |Z| \leq |X| \) and \( |Z| > |X| \) are handled separately.

- **Suppose \( |Z| \leq |X| \).** Therefore, the algorithm merges Y and Z.

In addition, suppose that \( \alpha|X| \geq |Y| + |Z| \). We claim that this implies case (A) holds. Indeed, (D-1) implies that condition (A-1) holds after the merge. The assumption \( \alpha|X| \geq |Y| + |Z| \) gives that (A-2) will hold. For (A-3), we argue by applying Lemma 32(d) with \( n₁ = |Y| \) and \( n₂ = |Z₁| + |Z₂| \) and \( n₃ = |Z₃| \) and with \( k + 2 \) in place of \( k \). For this, we need \( k + 2 \leq k₀(\alpha) + 1 \) as was already proved and also need

\[
\frac{2^{k+2}(2\alpha-1)}{\alpha - 1}|Z₃| \geq |Y| + |Z|.
\]
This is true by (D-7) since \(|Y| + |Z| < (1 + 1/\alpha)|Z|\) by (D-6) and since \(1 + 1/\alpha < 4\). We also have \(m_Z - 1 = m_{Z_1} + m_{Z_2} > 0\). Thus, Lemma 32(d) implies

\[ H_\alpha(|Y|, m_Y) + H_\alpha(|Z_1| + |Z_2|, m_{Z-1} + (k+2)|Z_3| + |Y| + 2(|Z_1| + |Z_2|) \leq G_\alpha(|Y| + |Z|, m_Y + m_Z). \]

Since \(\alpha < 2\), \(G_\alpha(|Y|, m_Y) \leq H_\alpha(|Y|, m_Y)\). Therefore, since \(|Z| = |Z_1| + |Z_2| + |Z_3|\),

\[ G_\alpha(|Y|, m_Y) + (k+1)|Z_3| + |Z_2| + H_\alpha(|Z_1| + |Z_2|, m_{Z-1} + |Y| + |Z| \leq G_\alpha(|Y| + |Z|, m_Y + m_Z). \]

Since the cost of merging \(Y\) and \(Z\) is equal to \(|Y| + |Z|\), this inequality plus the bound (D-8) implies that (A-3) will hold after the merge.

Alternately, suppose \(\alpha|X| < |Y| + |Z|\). In this case, \(Y\) and \(Z\) are merged: \(k\) will be incremented by 1 and \(Y\) will become part of \(Z_1\). We claim that case (D) still holds after the merge of \(Y\) and \(Z\). Clearly (D-1) still holds. (D-2) still holds with \(Z_1\) now including \(Y\). (That is, \(Y\) becomes \(U_{k+1}\).) (D-1) and (D-3) imply \(|X| \geq \alpha|Y| \geq \alpha^{k+1}|Z_3|\), so (D-3) will still hold. (D-4) implies \(|\frac{Y}{\alpha-1}| \geq |Z_1| + |Z_2|\). Therefore, (D-4) gives

\[ \frac{|X|}{\alpha - 1} \geq \frac{\alpha|Y|}{\alpha - 1} = \frac{|Y|}{\alpha - 1} \geq |Y| + |Z_1| + |Z_2|. \]

Thus (D-4) will still hold after the merge (since, after the merge, \(Y\) becomes part of \(Z_1\)). The hypothesis \(\alpha|X| < |Y| + |Z|\) implies (D-6) will still hold. By (D-6) we have \(|Z| >\alpha|Y| > |Y|\), so (D-7) gives

\[ |Z| + |Y| \leq 2|Z| \leq \frac{2^{k+1}(2\alpha-1)}{\alpha-1}|Z_3|. \]

Thus (D-7) will still hold. Finally, by (D-4), we may apply Lemma 32(a) with \(n_1 = |Y|\) and \(n_2 = |Z_1| + |Z_2|\) to obtain

\[ G_\alpha(|Y|, m_Y) + H_\alpha(|Z_1| + |Z_2|, m_{Z-1} + |Y| + |Z_1| + |Z_2| + |Z_3| \leq H_\alpha(|Y| + |Z_1| + |Z_2|, m_Y + m_Z - 1 + |Z_3|. \]

Since the cost of merging \(Y\) and \(Z\) is \(|Y| + |Z_1| + |Z_2| + |Z_3|\) and since \(k\) is incremented by 1 after the merge, this implies that (D-8) will still hold after the merge.

- Now suppose \(|Z| > |X|\), so \(\ell \geq 3\). In this case, algorithm merges \(X\) and \(Y\); the result becomes the second run on the stack, which we denote \((XY)\). We claim that immediately after this, the algorithm merges the combination \((XY)\) of \(X\) and \(Y\) with the run \(Z\). Indeed, since \(\varphi < \alpha\), we have \(\alpha > 1 + 1/\alpha\) and therefore by (D-6) and by the assumed bound on \(|X|\)

\[ \alpha|Z| > \frac{1}{\alpha^2}|Z| + |Z| > |Y| + |X|. \]

Thus, the test on line 6 of Algorithm 6 triggers a second merge operation. Furthermore, since \(\varphi < \alpha\), we have \(1 > \frac{1}{\alpha^2} + \frac{1}{\alpha^3}\) and thus, using (D-1), (D-3) and (D-4),

\[ |W| > \frac{1}{\alpha^{k+2}}|W| + \frac{1}{\alpha^2(\alpha-1)}|W| \geq \frac{1}{\alpha^k}|Y| + \frac{1}{\alpha-1}|Y| \geq |Z_1| + |Z_2| + |Z_3| = |Z|. \]

With \(|W| > |Z|\), the second merge acts to merge \((XY)\) and \(Z\) instead of \(W\) and \((XY)\). After the second merge, the top three runs \(X, Y, Z\) on the stack have been merged, with an additional merge cost of \(2|X| + 2|Y| + |Z|\). As we argue next, the algorithm now either transitions to case (A) or stays in case (D), depending whether \(\alpha|W| \geq |X| + |Y| + |Z|\) holds.
First, suppose that \( \alpha W \geq |X| + |Y| + |Z| \). We claim that this implies case (A) holds after the two merges. Indeed, (D-1) implies that condition (A-1) will hold. The assumption \( \alpha W \geq |X| + |Y| + |Z| \) gives that (A-2) will hold. For (A-3), we argue as follows. We apply Lemma 32(d) with \( n_1 = |X|+|Y| \) and \( n_2 = |Z_1|+|Z_2| \) and \( n_3 = |Z_3| \) and with \( k+2 \) in place of \( k \). For this, we need \( k+2 \leq k_0(\alpha) + 1 \) as was already proved and also need

\[
\frac{2^{k+2}(2\alpha-1)}{\alpha-1}|Z_3| \geq |X| + |Y| + |Z|.
\]

(16)

To prove (16), first note that that \( |X| + |Y| + |Z| < (2+1/\alpha)|Z| \) by (D-6) and the assumption that \( |Z| > |X| \); then (16) follows from (D-7) and the fact that \( 2 + 1/\alpha < 4 \). We have \( m_Z-1 = m_{Z_1} + m_{Z_2} > 0 \). Thus, Lemma 32(d) implies

\[
H_\alpha(|Y|+|X|, m_Y + m_X) + H_\alpha(|Z_1|+|Z_2|, m_Z-1) + (k+2) \cdot |Z_3| + |X| + |Y| + 2(|Z_1| + |Z_2|) \\
\leq G_\alpha(|X|+|Y|+|Z|, m_X + m_Y + m_Z).
\]

(17)

By (D-1), we have \( (\alpha-1)|Y| < \alpha|Y| \leq |X| \). Thus Lemma 32(a), with \( n_1 = |X| \) and \( n_2 = |Y| \) and \( m_1 = m_X \) and \( m_2 = m_Y \) gives

\[
G_\alpha(|X|, m_X) + H_\alpha(|Y|, m_Y) + |X| + |Y| \leq H_\alpha(|X|+|Y|, m_X + m_Y).
\]

(18)

Since \( \alpha < 2 \), \( G_\alpha(|Y|, m_Y) < H_\alpha(|Y|, m_Y) \). So, using \( |Z| = |Z_1|+|Z_2|+|Z_3| \), (17) and (18) imply

\[
G_\alpha(|X|, m_X) + G_\alpha(|Y|, m_Y) + (k+1)|Z_3| + |Z_2| + H_\alpha(|Z_1|+|Z_2|, m_Z-1) + 2|X|+2|Y|+|Z| \\
\leq G_\alpha(|X|+|Y|+|Z|, m_X + m_Y + m_Z).
\]

Since the cost of two merges combining \( X \), \( Y \) and \( Z \) was \( 2|X|+2|Y|+|Z| \), the last inequality and (D-8) imply that (A-3) will hold after the two merges.

Alternately, suppose \( \alpha W \geq |X| + |Y| + |Z| \). This implies \( \ell \geq 4 \). We claim that in this case (D) still holds after the two merges combining \( X \), \( Y \) and \( Z \), and with \( k \) incremented by 2. Certainly, (D-1) still holds. (D-2) is also still true: \( Z_2 \) and \( Z_3 \) are unchanged, and \( Z_1 \) will include \( X \) and \( Y \) (as \( U_{k+2} \) and \( U_{k+1} \)). (D-1) and (D-3) imply

\[
|W| \geq \alpha|X| \geq \alpha|Y| \geq \alpha^{k+2}|Z_3|,
\]

so (D-3) will still hold. (D-4) implies \( \frac{|Y|}{\alpha-1} \geq |Z_1|+|Z_2| \). Hence, (D-1) and (D-4) give

\[
\frac{|W|}{\alpha-1} \geq \frac{\alpha|X|}{\alpha-1} \geq \frac{|X|}{\alpha-1} + \frac{|X|}{\alpha} \geq \frac{\alpha|Y|}{\alpha-1} + \frac{|X|}{\alpha-1} + \frac{|Y|}{\alpha-1} \\
\geq \frac{|X| + |Y| + |Z_1|}{|X| + |Y| + |Z_2|};
\]

i.e., (D-4) will still hold. (D-5) is obviously still true. \( \alpha W \geq |X|+|Y|+|Z| \) implies (D-6) will still hold. The already proved equation (16) implies that (D-7) will still hold. Finally, we need to establish (D-8).

By (D-4), \( |Y| \geq (\alpha-1)(|Z_1|+|Z_2|) \); and by (D-1) and (D-3), \( |X| \geq \alpha|Y| \geq \alpha(\alpha-1)(|Y|+|Z_1|+|Z_2|) \). Therefore, we can apply Lemma 32(a) twice, first with \( n_1 = |X| \) and \( n_2 = |Z_1|+|Z_2| \) and then with \( n_1 = |X| \) and \( n_3 = |Y|+|Z_1|+|Z_2| \), to obtain

\[
G_\alpha(|X|, m_X) + G_\alpha(|Y|, m_Y) + H_\alpha(|Z_1|+|Z_2|, m_Z-1) + 2|X|+2|Y|+|Z| \\
< G_\alpha(|X|, m_X) + G_\alpha(|Y|, m_Y) + H_\alpha(|Z_1|+|Z_2|, m_Z-1) + |X|+2|Y|+2|Z| \\
\leq G_\alpha(|X|, m_X) + H_\alpha(|Y|+|Z_1|+|Z_2|, m_Y+m_Z-1) + |X|+|Y|+|Z_3| \\
\leq H_\alpha(|X|+|Y|+|Z_1|+|Z_2|, m_X+m_Y+m_Z-1) + 2|Z_3|
\]

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where the first inequality uses the assumption $|X| < |Z|$ and the other two inequalities use Lemma 32(a) and $|Z| = |Z_1| + |Z_2| + |Z_3|$. From this, it is easily seen that (D-8) will still hold after the two merges combining $X$, $Y$ and $Z$: this is because the additional merge cost is $2|X| + 2|Y| + |Z|$ and since $k$ will be incremented by 2.

This completes the proof of Theorem 21.

We can now prove Theorem 23.

**Proof of Theorem 23.** Examination of the conditions (A-1), (B-1), (C-1) and (D-1) for the proofs of Theorems 21 and 22 shows that the stack $X$ satisfies the following properties, for some $\ell' \geq 0$: 
(a) $|X_i| \geq \alpha|X_{i+1}|$ for all $i < \ell'$; and (b) The size $\ell$ of the stack $X$ equals either $\ell' + 1$ or $\ell' + 2$. The total of the run lengths of $X_1, \ldots, X_{\ell'}$ is

$$\sum_{i=1}^{\ell'} |X_i| \geq |X_{\ell'}| \cdot \sum_{i=0}^{\ell'-1} \alpha^i = \frac{\alpha^{\ell'} - 1}{\alpha - 1} \cdot |X_{\ell'}|$$

Therefore, the $\ell' + 1$ runs $X_1, \ldots, X_{\ell'+1}$ have total length at least $\frac{\alpha^{\ell'} - 1}{\alpha - 1} + 1$.

We will show that $\ell' \leq (2 - \alpha) + \log_\alpha n$; and that if $\ell' = (2 - \alpha) + \log_\alpha n$ then $\ell = \ell' + 1$. These together imply that the stack size $\ell$ is always $< (4 - \alpha) + \log_\alpha n$, and suffices to prove the theorem. Suppose, for sake of contradiction, that $\ell' > (2 - \alpha) + \log_\alpha n$.

$$\ell' > (2 - \alpha) + \log_\alpha ((\alpha-1)n).$$

From this, $\alpha^{\ell'} + \alpha - 2 > (\alpha - 1)n$. This gives $\frac{\alpha^{\ell'} - 1}{\alpha - 1} + 1 > n$, which is a contradiction since the total of the lengths of $X_1, \ldots, X_{\ell'+1}$ cannot be $\geq n$. This establishes $\ell' \leq (2 - \alpha) + \log_\alpha n$.

On the other hand, if $\ell' = 1 + \log_\alpha n$, then the same calculation shows that the total of the lengths of $X_1, \ldots, X_{\ell'+1}$ is $\geq n$, so $\ell = \ell' + 1$. 

\[\square\]

### 6 Experimental results

This section reports some computer experiments comparing the $\alpha$-stack sorts, the $\alpha$-merge sorts, Timsort, and the Shivers sort. The test sequences use the following model. We only measure merge costs, so the inputs to the sorts are sequences of run lengths (not arrays to be sorted). Let $\mu$ be a distribution over integers. A sequence of $m$ run lengths is chosen by choosing each of the $m$ lengths independently according to the distribution $\mu$. We consider two types of distributions:

1. The uniform distribution over numbers between 1 and 100,

2. A mixture of the uniform distribution over integers between 1 and 100 and the uniform distribution over integers between 10000 and 100000, with mixture weights 0.95 and 0.05. This distribution was specially tailored to work better with 3-aware algorithms.

We also experimented with power law distributions. However, they gave very similar results to the uniform distribution so we do not report these results here.

In Figures 1 and Figure 2, we estimate the “best” $\alpha$ values for the $\alpha$-merge sort and the $\alpha$-stack sort under the uniform distribution. The experiments show that the best value for $\alpha$ for both types of algorithms is around the golden ratio, or even slightly lower. For $\alpha$ at or below $\varphi$, the results start to show more and more oscillation. We do not know the reason for this oscillation.

Next we compared all the stable merge sorts discussed in the paper. Figure 3 reports on comparisons using the uniform distribution. It shows that the 1.62-merge sort performs slightly
Figure 1: Comparison between $\alpha$-merge sorts for different $\alpha$ on uniform distribution over integers between 1 and 100.

Figure 2: Comparison between $\alpha$-stack sorts for different $\alpha$ on uniform distribution over integers between 1 and 100.
better than the 1.62-stack sort; and they perform better than Timsort, the 2-stack sort and the
2-merge sort. The Shivers sort performed comparably to the 1.62-stack sort and the 1.62-merge
sort, but exhibited a great deal of oscillation in performance, presumably due to its use of rounding
to powers of two.

Figure 4 considers the mixed distribution. Here the 1.62-merge sort performed best, slightly
better than the 2-merge sort and Timsort. All three performed substantially better the 1.62-stack
sort, the 2-stack sort, and the Shivers sort.

7 Conclusion and open questions

Theorem 21 analyzed the $\alpha$-merge sort only for $\alpha > \varphi$. This leaves several open questions:

**Question 33.** For $\alpha \leq \varphi$, does the $\alpha$-merge sort run in time $c_\alpha(1+\omega_m(1))n \log m$?

It is likely that when $\alpha < \varphi$, the $\alpha$-merge sort could be improved by making it 4-aware, or more
generally as $\alpha \rightarrow 1$, making it $k$-aware for even larger $k$’s.

**Question 34.** Is it necessary that the constants $d_\alpha \rightarrow \infty$ as $\alpha$ approaches $\varphi$?

An augmented Shrivers sort can defined by replacing the inner while loop on lines 6-8 with the
code:

```plaintext
while $2^{\lfloor \log |Y| \rfloor} \leq |Z|$ do
  if $|Z| \leq |X|$ then
    Merge $Y$ and $Z$
  else
    Merge $X$ and $Y$
  end if
end while
```
Figure 4: Comparison between sorting algorithms using a mixture of the uniform distribution over integers between 1 and 100 and the uniform distribution over integers between 10000 and 100000, with mixture weights 0.95 and 0.05

The idea is to incorporate the 3-aware features of the 2-merge sort into the Shrivers sort method. The hope is that this might give an improved worst-case upper bound:

**Question 35.** Does the augmented Shrivers sort run in time $O(n \log m)$? Does it run in time $(1+o_m(1))n \log m$?

The notation $o_m(1)$ is intended to denote a value that tends to zero as $m \to \infty$.

An lower or upper bound in the form $n \log m$ for the running time of Timsort is not known:

**Question 36.** Does Timsort run in time $O(n \log m)$?

We may define the “optimal stable merge cost” of an array $A$, denoted $\text{Opt}(A)$, as the minimal merge cost of the array $A$ over all possible stable merge sorts. It is not hard to see that there is a quadratic time $m$-aware optimal stable merge sort, which first determines all $m$ run lengths and then works somewhat like dynamic programming. But for awareness less than $m$ we know nothing.

**Question 37.** Is there a $k$-aware algorithm for $k = O(1)$ or even $k = O(\log m)$ such that for any array $A$ this algorithm has merge cost $(1+o_m(1))\text{Opt}(A)$?

Our experiments used random distributions that probably do not do a very good job of modeling “real-world data.” Is it possible to create better models for real-world data? Finally, it might be beneficial to run experiments with actual real-world data, e.g., by modifying deployed sorting algorithms to calculate statistics based on run lengths that arise in actual practice.

**References**


