# Polynomial-Time Verification and Testing of Implementations of the Snapshot Data Structure

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#### Abstract

We analyze correctness of implementations of the snapshot data structure in terms of linearizability. We show that such implementations can be verified in polynomial time. Additionally, we identify a set of representative executions for testing and show that the correctness of each of these executions can be validated in linear time. These results present a significant speedup considering that verifying linearizability of implementations of concurrent data structures, in general, is EXPSPACE-complete in the number of program-states, and testing linearizability is NP-complete in the length of the tested execution. The crux of our approach is identifying a class of executions, which we call simple, such that a snapshot implementation is linearizable if and only if all of its simple executions are linearizable. We then divide all possible non-linearizable simple executions into three categories and construct a small automaton that recognizes each category. We describe two implementations (one for verification and one for testing) of an automata-based approach that we develop based on this result and an evaluation that demonstrates significant improvements over existing tools. For verification, we show that restricting a state-of-the-art tool to analyzing only simple executions saves resources and allows the analysis of more complex cases. Specifically, restricting attention to simple executions finds bugs in 27 instances, whereas, without this restriction, we were only able to find 14 of the 30 bugs in the instances we examined. We also show that our technique accelerates testing performance significantly. Specifically, our implementation solves the complete set of 900 problems we generated, whereas the state-of-the-art linearizability testing tool solves only 554 problems.

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Related Version Full Version: https://github.com/hayounav/Thesis\_experiments/blob/main/snapshot verification and testing/Polynomial\_time\_verification\_of\_snapshot\_implementations\_DISC\_.pdf

Supplementary Material Software (Source Code): https://github.com/hayounav/Thesis\_experiments; archived at swh:1:dir:10be8bad714e0da40fec5d0a1a6aa34c550ccc33

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## 1 Introduction

As concurrency is very effective for accelerating the performance of computer programs, there is much scientific research and practical attention on the design, implementation, and verification of data structures that allow parallel access. We focus on the well-known *snapshot* 

data structure which is an essential building block of distributed arrays [4,7,9]. This data structure allows asynchronous processes to write values to a shared array of single-writer registers, by executing update operations, and to take instantaneous snapshots of the array values, by executing scan operations. It is useful for allowing processes to share information while maintaining a correct joint view of the data.

For proving the correctness of implementations of the snapshot data structure, we consider the standard *linearizability* [31] condition. Roughly speaking, linearizability is the requirement that for every execution of a given implementation, the procedure executions can be ordered linearly such that (a) the resulting linear order is consistent with the definition of the data structure; (b) it preserves the precedence of procedure executions in time. In the specific case of snapshot, the definition of the data structure is that a sequential (linear) execution is correct if every scan operation reports the value written by the last update operation of each of the processes. Linearizability is widely accepted as a correctness criterion since, effectively, it formulates the requirement that procedure executions are seen to a user as if they were executed one after the other (i.e., atomically).

Automatic verification of linearizability is known to be computationally expensive. The verification of finite-state implementations is EXPSPACE-complete in the number of program states [5, 29] and undecidable for infinite-state implementations [14]. Testing linearizability, i.e., deciding whether a given execution is linearizable, is NP-complete [28]. These complexities do not stop the community from pursuing effective verification and testing techniques, because it is very difficult to provide correct implementations of concurrent data structures; bugs have been found in both academic and deployed implementations [18, 20, 42]. These made it clear that there is an acute necessity for reliable verification and testing techniques.

One commonly used technique is the *linearization points* based verification approach, which often does not work in the case of snapshot. A linearization point of a procedure execution is an action that represents the moment at which the procedure "actually occurs". Once fixed linearization points are identified, verifying linearizability becomes PSPACE-complete [14]. Unfortunately, snapshot implementations do not usually admit fixed linearization points (e.g., all twelve published implementations listed in [35] do not admit such points). Researchers also suggested using linearization points as an optimization: ask the user to provide them (whether fixed or conditional) and use this information to accelerate verification [3,6,13,50]. However, practice shows that it is difficult to find and specify the linearization points of snapshot implementations, even in a conditional manner. One difficulty is that the linearization points of scan operations often belong to other, parallel, procedure executions (see [4,11,46]).

In this paper, we propose an effective polynomial-time technique for verifying snapshot implementations, and an effective linear-time technique for testing snapshot executions. The crux of our techniques is an optimization approach that exponentially reduces the number of reachable program states. Specifically, we prove that if an algorithm is data-independent [54] then, in order to verify its correctness, it suffices to consider only a small fraction of its executions which we call *simple*.

The simple executions that we focus on are those in which:

- 1. All but two processes invoke only  $\mathsf{update}(v_0)$  and  $\mathsf{scan}$  operations, where  $v_0$  is the initial value of the array segments. In other words, n-2 of the n processes are not allowed to change the initial value in their segments;
- 2. Each of the two remaining processes may only change their data value once, to a predetermined value: it executes only  $\mathsf{update}(v_0)$  and  $\mathsf{scan}$  operations up to an arbitrary point in the execution, after which it transitions to executing only  $\mathsf{update}(v_1)$  and  $\mathsf{scan}$  operations, where  $v_1 \neq v_0$  are fixed data values.

The focus on simple executions reduces the number of reachable states significantly, as n-2 entries of the array are essentially constants (see Section 3).

After showing that it is enough to verify the correctness of simple executions, we continue and show that every non-linearizable simple execution falls into one of three categories that we identify. Moreover, we show that each of these three possible bug patterns can be recognized by an automaton with at most n states and  $n^2$  transitions (see Section 4). This enables verifying linearizability of snapshot implementations via a reachability check applied to the graph product of the implementation and the automatons where the target states of the reachability are the automatons' accepting states. As there are  $O(n^2)$  combinations to choose the two excluded processes, snapshot implementations can be verified with this method in time  $O(mn^4)$  where m is the number of reachable states via simple executions (which is significantly smaller than the number of reachable states via all executions). Furthermore, by feeding a simple execution to these automatons, an execution of length l can be tested in time O(l). As it is sufficient to consider simple executions, this effectively means that snapshot executions can be tested in linear-time (see Section 5).

We have implemented and evaluated the proposed verification and testing techniques and ran them against state-of-the-art tools. For verification, we compared with the PAT [44] model checker. The results show that our approach allows deeper exploration of implementations from the literature. This allowed us to detect 27 of 30 inserted bugs, compared to 16 found by the baseline method. Furthermore, we managed to verify an algorithm by Bowman [17] for three and four processes, whereas the baseline method failed to do so. For testing, we compared with the linearizability testing tool proposed by Lowe [41]. The results show that our testing technique is robust and scalable and that it can cope with much longer histories than the baseline (see Section 7).

Due to lack of space, we give proof sketches and skip technical details. We provide a full version with complete proofs, and means to reproduce the experiments in the paper supporting materials [49].

#### 2 Preliminaries

This section presents definitions and notations used throughout this paper. We provide further definitions, required for all complete proofs, and extended discussions in the supporting materials [49, Appendix A].

Let Vals be an infinite set of abstract data values, and let  $v_0 \in Vals$  be the distinguished value used to initialize the segments of a snapshot. For  $n \in \mathbb{N}$ , let  $p_0, \ldots, p_{n-1}$  be processes. We model an execution of a snapshot algorithm by the processes as a sequence of actions. Among the actions the processes perform, we are interested in the invocations and responses of procedure executions. For process  $p_i$  and data values  $u, u_0, \ldots, u_{n-1}$ ,  $inv.update_i(u)$ ,  $res.update_i$ ,  $inv.scan_i$ ,  $res.scan_i(u_0, \ldots, u_{n-1})$  are  $p_i$ -actions. Let  $\Sigma$  be the set of all such actions.

Throughout the paper, we refer to these actions using general terms such as: an update invocation, a scan response, a  $p_i$ -invocation etc., which are defined in a straightforward manner. For example, we may say that the action  $res.scan_i(u_0, \ldots, u_{n-1})$  is a scan response, or a  $p_i$ -action, etc.

A history is a word h over  $\Sigma$  that exhibits the following properties:

- 1. For every process  $p_i$ , the first  $p_i$ -action in h, if any, is a  $p_i$ -invocation.
- 2. For every  $p_i$ -update (respectively, scan) invocation in h, the following  $p_i$ -action in h, if any, is a  $p_i$ -update (respectively, scan) response.
- 3. For every  $p_i$ -response in h, the following  $p_i$ -action, if any, is a  $p_i$ -invocation.

**Figure 1** A linearizable history.  $U_2$ ,  $S_1$  are complete, while  $U_1$ ,  $S_2$  are pending ops.

An operation is an execution of an update/scan procedure. We identify operations in histories with their invocation and response actions. Operations that do not return are identified by their invocation alone.

A complete operation in a history  $h = \alpha_0 \cdots \alpha_m$  is a pair of actions,  $(\alpha_k, \alpha_l)$ , where k < l,  $\alpha_k$  is an  $\mathsf{update}_i$  (respectively,  $\mathsf{scan}_i$ ) invocation,  $\alpha_l$  is an  $\mathsf{update}_i$  (respectively,  $\mathsf{scan}_i$ ) response, and there is no  $p_i$ -action in between. A pending operation in h is a single action,  $(\alpha_k)$ , where  $\alpha_k$  is a  $p_i$ -invocation, and there is no  $p_i$ -action that follows  $\alpha_k$  in h.

Similarly to actions, we refer to operations using general terms: an operation O is, e.g., a  $p_i$ -operation, an update operation, a  $\mathsf{scan}_i(u_0, \dots, u_{n-1})$  operation, etc. In a history h, for an  $\mathsf{update}(u)$  operation U, we write  $val_h(U) = u$ , and for a  $\mathsf{scan}(u_0, \dots, u_{n-1})$  operation S and i < n, we write  $val_{h:i}(S) = u_i$  and  $val_h(S) = (u_0, \dots, u_{n-1})$ .

For a complete operation  $A = (\alpha_k, \alpha_l)$  and an operation  $B \in \{(\alpha_m, \alpha_t), (\alpha_m)\}$  in a history  $h = \alpha_0 \alpha_1 \cdots$ , we write  $A <_h B$  if l < m. Clearly,  $<_h$  is a partial order over the operations in h, in which pending operations are maximal elements. Figure 1 illustrates a two-process history with pending and complete operations.

Linearizability [31] is the standard correctness condition for concurrent data structures. Roughly speaking, a history h is linearizable if the partial ordering  $<_h$  can be extended to a linear ordering that satisfies the sequential specification of the snapshot data structure. That is, each scan operation S returns in each entry i the value written by the maximal  $\mathsf{update}_i$  operation that precedes it. The extension should include all complete operations, and each pending operation is either completed or omitted.

We now turn to define the linearizability condition formally:

- ▶ **Definition 1.** A history h is linearizable if it can be extended into a history h' by appending zero or more response events to h, such that there exists a linear ordering  $\prec_{h'}$  of the complete operations in h' that satisfies the following conditions:
- **1.** For  $A, B \in h$ , if  $A <_h B$ , then  $A \prec_{h'} B$ .
- 2. If  $S \in h'$  is a scan operation and  $U_i \in h'$  is the maximal update, operation such that  $U_i \prec_{h'} S$ , then  $val_h(U_i) = val_{h:i}(S)$ . If no update, operation precedes S in h', then  $val_{h:i}(S) = v_0$ .

Any  $\prec_{h'}$  that satisfies these conditions is said to be a linearization of h.

▶ Example 2. The history depicted in Figure 1 is linearizable by the order  $U_1 \prec_h U_2 \prec_h S_1$ . To obtain a linearization, we completed the pending operation  $U_1$ , as its value is read by  $S_1$ . However, we chose to omit the pending scan operation  $S_2$ .

Our main goal is to analyze the linearizability of snapshot algorithms, defined as follows:

▶ **Definition 3** (Snapshot Linearizability). *A snapshot algorithm is linearizable if all of its histories are linearizable.* 

The data independence property, proposed by Wolper [54], roughly means that the behavior of an algorithm does not depend on the data values passed as arguments to the procedure executions. The formal definition employs the notion of a renaming: a function  $f: Vals \longrightarrow Vals$ . An algorithm is data-independent if for a every history h of the algorithm and a renaming f: (1) the history f(h), obtained by replacing each data value u with f(u), is also a history of the algorithm; and (2) if h = f(h'), then h' is a history of the algorithm. See full version [49] for more details.

Data independence is natural to assume, as snapshot implementations synchronize accesses to a shared resource and thus are expected to be value-agnostic. This is substantiated by all twelve different published implementations [4,7–11,26,34–36,46] listed in [35].

Finally, a history is *differentiated* if no two update operations in it were invoked with the same data value.<sup>1</sup> Abdulla et al. [1] showed that it is sufficient to consider *differentiated* histories to prove linearizability of data-independent algorithms.

## 3 Simple Histories

In this section, we identify a set of histories, which we name *simple*. We then prove that a data-independent snapshot implementation is linearizable if and only if all of its simple histories are linearizable. Therefore, this section shows that it is sufficient to consider only some histories to determine the linearizability of data-independent snapshot implementations.

In a simple history, the update operations are invoked with only two distinct values. The first is the initial value  $v_0$ , and without loss of generality, we take some other  $v_1 \in Vals$  as the second value. All but two processes invoke only update( $v_0$ ) and scan operations. The remaining two execute only update( $v_0$ ) and scan operations, and at some (possibly different) point, each of the two processes shifts to executing only update( $v_1$ ) and scan operations.

- ▶ **Definition 4** (Simple histories). A history h of n processes is (i, j)-simple for i < j < n, if there are  $r_i, r_j \in \mathbb{N}$  such that the following conditions hold:
- 1. Let U be the r-th  $update_i$  operation in h. If  $r < r_i$ , then U is an  $update_i(v_0)$  operation, and if  $r \ge r_i$ , then U is an  $update_i(v_1)$  operation.
- 2. In the same way, let U be the r-th update<sub>j</sub> operation in h. If  $r < r_j$ , then U is an update<sub>j</sub> $(v_0)$  operation, and if  $r \ge r_j$ , then U is an update<sub>j</sub> $(v_1)$  operation.
- **3.** Any  $\mathsf{update}_k$  operation is an  $\mathsf{update}_k(v_0)$  operation, if  $k \notin \{i, j\}$ . A history h is simple if it is (i, j)-simple for some i < j < n.

We are ready to prove the sufficiency of focusing on simple histories. We provide a proof sketch below, and give a rigorous proof in the full version [49].

▶ **Theorem 5.** A data-independent snapshot algorithm  $\mathcal{L}_{nap}$  is linearizable if and only if all its simple histories are linearizable.

**Proof sketch.** Anderson's shrinking lemma identifies five properties that are equivalent to the linearizability of a snapshot history [8]. To prove the non-trivial direction of theorem 5 ('if'), we assume that  $\mathcal{L}_{nap}$  is not linearizable. Consider some non-linearizable differentiated history h. Since  $\mathcal{L}_{nap}$  is not linearizable, h violates (at least) one of the shrinking lemma's properties. Based on the violated property, we construct a renaming  $f: Vals \to \{v_0, v_1\}$ , and apply it to h to obtain a non-linearizable simple history.

<sup>&</sup>lt;sup>1</sup> For generating differentiated histories, a minor modification is required: we should allow different initial values for the array segments. See comment in full version [49, Appendix B]

- **Figure 2** The k-th interval of S,  $I_k(S)$ .
- ▶ Remark 6. In the context of simple histories, scan operations return  $v_0$  in all entries except for entries i and j. Thus, for the remainder of this paper, we use  $res.scan_k(u_i, u_j)$  as shorthand for  $res.scan_k(v_0, \ldots, v_0, u_i, v_0, \ldots, v_0, u_j, v_0, \ldots, v_0)$ .
- ▶ Remark 7. From this point on, for readability, we will use 0 and 1 instead of  $v_0$  and  $v_1$ , respectively.

## 4 A Simple Condition for the Linearizability of Simple Histories

In this section, we formulate three properties that are equivalent to the linearizability of an (i, j)-simple history. We then show that the negation of each property is regular, and present a construction of a matching automaton. Before providing our properties (in upcoming Theorem 10), we discuss each intuitively and explain why it is mandatory for linearizability.

**Property 1: No Inversion.** Assume that a scan operation  $S_1$  returns 0 at the *i*th entry (for example), while  $S_2$  returns 1. This indicates that  $S_2$  read a more recent value from the *i*th segment. Hence, in any linearization,  $S_1$  must precede  $S_2$ . As the same reasoning goes for the *j*th entry, it is forbidden for  $S_1$  to return 0 and 1 at the *i*th and jth entries, while  $S_2$  returns the opposite values.

**Property 2: Non-Decreasing.** If a scan operation  $S_1$  precedes a scan operation  $S_2$ , then  $S_2$  must obtain more recent values from all array segments. Therefore, it is forbidden for  $S_1$  to return 1 in entry  $k \in \{i, j\}$ , while  $S_2$  returns 0 in its kth entry.

**Property 3: Appropriateness.** We require that for each scan operation there are "appropriate" update operations,  $U_i$  by  $p_i$  and  $U_j$  by  $p_j$ , that we can linearize before S. "Appropriate" means that the next three conditions hold.

First condition. The timings of the update operations must not prevent them from being linearized before S. For example, they must not succeed S. Formally, we require that they belong to the *interval of* S, defined below and illustrated in Figure 2:

- ▶ **Definition 8.** Let S be a scan operation in a history h, and let k < n. The kth interval of S, denoted  $I_k(S)$ , is the set of update<sub>k</sub> operations U ∈ h such that:
- 1.  $\neg (S <_h U)$ .
- 2. There is no update<sub>k</sub> operation U' such that  $U <_h U' <_h S$ .

**Second condition.** The values of the update operations  $U_i$  and  $U_j$  are the values returned by S in its corresponding entries.

**Third condition.** There is no, e.g.,  $\mathsf{update}_i$  operation between  $U_i$  and  $U_j$ . This is because the existence of such an  $\mathsf{update}_i$  operation, say  $U_i < U_i' < U_j$ , would prevent us from linearizing both  $U_i$  and  $U_j$  before S.

We formalize the notion of appropriateness in the following definition:

- ▶ **Definition 9.** Let S be a complete scan operation in an (i,j)-simple history h. A pair  $(U_i, U_j)$  where  $U_i$  is an  $update_i$  operation and  $U_j$  is an  $update_j$  operation, is said to be S-appropriate, if:
- **1.**  $U_i \in I_i(S)$  and  $U_j \in I_j(S)$ .
- **2.**  $(val_h(U_i), val_h(U_j)) = (val_{h:i}(S), val_{h:j}(S)).$
- 3. There is no update<sub>i</sub> operation  $U'_i$  such that  $U_i < U'_i < U_j$ , and there is no update<sub>j</sub> operation  $U'_i$  such that  $U_j < U'_i < U_i$ .

So far, we have presented our properties and explained intuitively why they form a necessary condition for linearizability: i.e., why their negation prevents linearizability. The main theorem of this section asserts a much stronger claim: these properties also constitute a sufficient condition for linearizability. We provide a proof for Theorem 10 in the full version [49, Appendix D].

▶ **Theorem 10.** An (i, j)-simple history h is linearizable if and only if the following properties hold.

**No Inversion.** There are no complete scan operations  $S_1$  and  $S_2$  in h such that  $(val_{h:i}(S_1), val_{h:j}(S_1)) = (0, 1)$  and  $(val_{h:i}(S_2), val_{h:j}(S_2)) = (1, 0)$ .

**Non-Decreasing.** If  $S_1$  and  $S_2$  are two complete scan operations in h such that  $S_1 <_h S_2$ , then  $val_{h:i}(S_1) \leq val_{h:i}(S_2)$  and  $val_{h:j}(S_1) \leq val_{h:j}(S_2)$ .

**Appropriateness.** For each complete scan operation S in h, there exists an S-appropriate pair of update operations.

## 4.1 Detecting Incorrect Simple Histories

Finally, we show that the properties of Theorem 10 can be detected by an NFA. We provide here proof sketches for most claims, and full proofs for all claims in the full version [49, Appendix E].

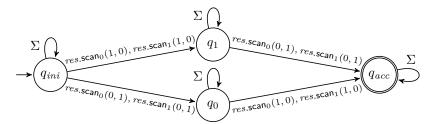
▶ **Theorem 11.** For i < j < n, there exists an automaton M with O(n) states and  $O(n^2)$  transitions, such that an (i, j)-simple history h is not linearizable if and only if  $h \in L(M)$ .

To prove Theorem 11, we construct automatons that detect violations of the three properties presented in Theorem 10.

#### 4.1.1 Detecting Violations of No-Inversion

▶ Proposition 12. There exists an automaton  $M_1$  such that, for any (i, j)-simple history h, h violates No-Inversion if and only if  $h \in L(M_1)$ . Moreover,  $M_1$  has O(1) states and O(n) transitions.

**Proof sketch.** We demonstrate the construction for the case that n=2:



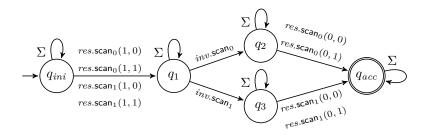
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## 4.1.2 Detecting Violations of Non-Decreasing

▶ Proposition 13. There exists an automaton  $M_2$  such that, for any (i, j)-simple history h, h violates Non-Decreasing if and only if  $h \in L(M_2)$ . Moreover,  $M_2$  has O(n) states and  $O(n^2)$  transitions.

**Proof sketch.** As an illustrative demonstration, we present below a simpler automaton. It detects the existence of a violation of Non-Decreasing, for n = 2, and  $S_1 < S_2$  where  $val_{h:i}(S_1) = 1$ .

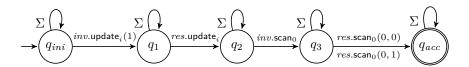


## 4.1.3 Detecting Violations of Appropriateness

It remains to construct an automaton that accepts all (i, j)-simple histories that violate Appropriateness. To this end, we reformulate Appropriateness as a regular safety property; a word is rejected if and only if it has a "bad"-prefix.

- ▶ Lemma 14. Let h be an (i,j)-simple history, and let S be a complete scan operation in h. For  $l \in \{i,j\}$ , let  $F_l$  be the first  $\operatorname{update}_l(1)$  operation in h, if exists. Then, there is no S-appropriate pair in h if and only if any of the following holds:
- **1.** For  $l \in \{i, j\}$ ,  $F_l$  exists,  $val_{h:l}(S) = 0$ , and  $F_l <_h S$ .
- **2.** For  $l \in \{i, j\}$ ,  $val_{h:l}(S) = 1$ , and either  $S <_h F_l$  or  $F_l$  doesn't exist.
- **3.**  $(val_{h:i}(S), val_{h:j}(S)) = (0,1)$  and  $F_i <_h F_j$ .
- **4.**  $(val_{h:i}(S), val_{h:j}(S)) = (1,0)$  and  $F_j <_h F_i$ .
- ▶ Proposition 15. There exists an automaton  $M_3$  such that, for any (i, j)-simple history h, h violates Appropriateness if and only if  $h \in L(M_3)$ . Moreover,  $M_3$  has O(n) states and  $O(n^2)$  transitions.

**Proof sketch.** The automaton is a "union" of four automatons, such that the kth automaton checks whether there exists a complete scan operation S for which the kth case of Lemma 14 holds. Below, we provide an automaton that identifies the first case where l=i and S is a scan<sub>0</sub> operation (for n=2). Hence, in fact, the first case is a union of 2n automatons. We leave it for the reader to verify that (rather simple) automatons exist for all other cases.



▶ Corollary 16. Theorem 11 is trivially correct by propositions 12, 13, and 15.

## Verifying and Testing Linearizability

The results of the previous section allow us to both verify data-independent snapshot implementations, and test the linearizability of simple snapshot histories, in polynomial time.

For verifying a data-independent snapshot implementation, by Theorem 5, it is sufficient to verify that all of its simple histories are linearizable. Theorem 11 allows one to apply model checking of regular properties [12, Chapter 4.2], i.e., one can check whether the implementation admits an (i, j)-simple history accepted by the automaton (and thus not linearizable). As there are  $O(n^2)$  valuations for i and j, our first key result follows:

▶ **Theorem 17** (Polynomial-time verification). Let  $\mathcal{L}_{nap}$  be a data-independent snapshot algorithm such that only finitely many states of  $\mathcal{L}_{nap}$  are reachable by its simple histories. Determining the linearizability of  $\mathcal{L}_{nap}$  is decidable in  $O(mn^4)$  time, where m is the size of an automaton that accepts all simple histories of  $\mathcal{L}_{nap}$ .

Moreover, Theorem 11 enables the testing of simple histories efficiently, by feeding the automaton of Theorem 11 (or its determinization) with the (i, j)-simple histories to be tested. The automaton will report acceptance once it identifies a non-linearizable prefix of the input history h (which testifies that h is not linearizable). Hence, our second key result follows.

▶ **Theorem 18** (Linear-time testing). For i < j < n, (i, j)-simple histories can be tested in linear-time, i.e., in time O(|h|).

## 6 Optimization: Omitting Redundant Commands

The focus on simple histories yields an optimization that can significantly reduce the state space of an examined snapshot algorithm, speeding up its verification. The optimization relies on the observation that in the executions of (i, j)-simple histories, some commands are vacuous. To elaborate, assume that register R stores the data value of process  $p_k$ ,  $k \neq i, j$ . In all executions of (i, j)-simple histories, R will only ever store the value 0. Thus, read and write commands from and to R can be ignored, reducing the possible values of the program counters. In some cases, we can even ignore R altogether, reducing the number of registers.

We use Bowman's obstruction-free snapshot algorithm [17] (Algorithm 1) to demonstrate the optimization. During an update operation, process  $p_k$  writes its new value to register A[k] (line 3). During a scan operation, the values stored in  $A[0], \ldots, A[n-1]$  are read into the local variables  $a[0], \ldots, a[n-1]$  (lines 7-8). Let i < j be two process ids, and consider executions of (i, j)-simple histories of Algorithm 1. In such executions, every write command to register  $A[k], k \notin \{i, j\}$ , writes 0. Hence, we may ignore and omit all registers  $A[k], k \notin \{i, j\}$ . This yields a simplified version of the algorithm, as shown in Algorithm 2, which has a substantially smaller state space than Algorithm 1, as it employs fewer registers. Since we omitted only vacuous commands (i.e. commands that always write and read 0) Algorithm 2 is linearizable if and only if all of Algorithm 1's (i, j)-simple histories are linearizable.

## 7 Implementation and Evaluation

In this section, we describe implementations of the procedures described in Section 5, and the experiments we performed to evaluate their efficiency. We provide the means to reproduce all experiments in the paper's supporting materials [49].

```
Algorithm 1 Unoptimized algorithm.
                                                             Algorithm 2 Optimized for (i, j)-simple executions.
 1: procedure update_{k}(v)
                                                              1: procedure update<sub>1</sub>.
                                                                                                                         \triangleright k \notin \{i, j\}
          Active \leftarrow \bot
                                                                       Active \leftarrow \bot
 2:
                                                              2:
          A[k] \leftarrow v
 3:
                                                              3: procedure update_r(v)
                                                                                                                         \triangleright r \in \{i, j\}
                                                                       Active \leftarrow \bot
 4: procedure scank
                                                              4:
                                                                       A[r] \leftarrow v
                                                              5:
          repeat
 5:
               Active \leftarrow k
 6:
               for \ell = 0, \dots, n{-}1 do
 7:
                                                              6: procedure scan<sub>a</sub>
                                                                                                                              \triangleright q < n
 8:
                   a[l] \leftarrow A[l]
                                                              7:
                                                                       repeat
                                                              8:
                                                                            Active \leftarrow q
          \mathbf{until}\ Active = k
 9:
                                                              9:
                                                                            a[i] \leftarrow A[i]
          return (a[0], ..., a[n-1])
10:
                                                             10:
                                                                            a[j] \leftarrow A[j]
                                                                       until Active = q
                                                             11:
                                                             12:
                                                                       return (0, \ldots, 0, a[i], 0, \ldots, 0, a[j], 0, \ldots, 0)
```

Figure 3 Illustration of the redundant command omission optimization with Bowman's algorithm.

#### 7.1 Implementation of our Verification Procedures

We used the model checker PAT [44] as the basis for our two verification approaches. PAT contains a system for checking the linearizability of a given concurrent algorithm against an abstract specification, via refinement [38,40]. We made use of this system in our first verification approach: we encoded known snapshot algorithms from the literature (listed in subsection 7.4), modified to admit only simple histories. We provided a matching abstract simple-history snapshot specification.

For our second approach, we encoded the automaton from Theorem 11 in PAT. As that automaton is a union of several automatons, we treated each one as a separate process, and encoded the union as the parallel composition of these processes. We exploited PAT's reachability checker to encode the accepting states of the automaton. We then asked PAT to check whether the algorithms listed in subsection 7.4 admit any simple histories that are accepted by the automaton.

We note three sources of possible errors in our implementations: (1) We could have encoded the snapshot algorithms incorrectly. (2) We could have encoded the automatons or the abstract specification incorrectly. (3) PAT itself may have bugs. To mitigate the first two threats, we used PAT's linearizability system to ensure that the algorithms we encoded are linearizable, that we manage to find several artificially-inserted bugs, and that the reachability approach agrees with PAT's standard refinement approach. We did not take steps to mitigate the third threat, but as PAT is a widely used model checker which has itself been partially model-checked [48], our confidence in its correctness is high., our confidence in its correctness is high.

#### 7.2 Implementation of our Testing Procedure

The testing procedure we implemented receives an (i, j)-simple history, and runs it through an implementation of the automaton described in Theorem 11. The tool announces whether the automaton accepts the history, indicating it is not linearizable, or it rejects the history, indicating it is linearizable.

To validate that our implementation has no bugs, we generated hundreds of random simple histories, both linearizable and non-linearizable, and ensured our implementation classified them correctly.

#### 7.3 Research Questions

We start with research questions related to our verification technique. As we propose a model checking approach, although polynomial, it still suffers from the state explosion problem [23]. This holds since the algorithms we check admit an enormous number of states, even when we restrict ourselves to simple histories. Model-checking approaches are mainly evaluated based on their feasibility; their ability to verify correctness/find bugs, perhaps only up to a reasonable depth, measured in the number of operations each process executes, with real-world resources: realistic time and space and limitations. Hence, we formulate the following research questions:

**RQ1** Does the focus on simple histories help to prove/disprove correctness, in terms of feasibility/depth to be processed?

**RQ2** Is our polynomial-time technique efficient for proving/disproving correctness, in terms of feasibility/depth to be processed?

We use the following research question to evaluate our testing technique:

RQ3 Is our testing technique efficient, in terms of feasibility, and time and space consumption?

#### 7.4 Corpus

To address RQ1 and RQ2, we constructed a corpus for our experiments that includes several snapshot algorithms from the literature: An obstruction-free [30] algorithm by Bowman [17], denoted BOWMAN; A snapshot algorithm by Jayanti [35], denoted JAYANTI; The bounded and unbounded versions of Afek et al. [4], denoted AFEK1 and AFEK2, respectively; and A snapshot algorithm by Riany et al [46], denoted RIANY.

For each algorithm and  $n \in \{3,4,5,6\}$  processes, we encoded the original version (denoted "full"), as well as a modified version which generates only (0,1)-simple histories, with the optimization detailed in Section 6 (denoted "simple-only"). Then, for  $n \in \{3,4,5,6,8,10\}$ , we also encoded buggy versions thereof (denoted, "buggy-full" and "buggy-simple-only", respectively). Overall, we created 100 configurations of pairs of algorithm encoding with n processes.

To address RQ3, we began by generating 25 linearizable histories of length  $l \in \{200, 500, 1000\}$  with  $n \in \{5, 8, 11, 14, 17, 20\}$  processes, by randomly executing an atomic snapshot implementation, and recording its actions. We then generated 25 non-linearizable histories of length  $l \in \{50, 100, 200\}$  with  $n \in \{3, 4, 5, 6, 8, 10\}$  processes as follows: we generated a random linearizable history, and changed its 20-length suffix by randomly changing the values of the scan responses. We repeated this process until we obtained 25 non-linearizable histories. In the context of RQ3, we refer to a choice of l, n, and "linearizable/non-linearizable" as a configuration. This resulted in 900 histories, divided into 18 linearizable and 18 non-linearizable configurations, added to our corpus.

#### 7.5 Experiments and Results

In this section, we detail the experiments we performed to tackle our research questions, and report our results. All experiments were performed on a rather ordinary laptop with an Intel Core i7-6820HK CPU and 32GB of DDR4 RAM, running Windows 10 21H1 and the WSL2 Ubuntu 20.04.2 image from Microsoft.

<b>Table 1</b> Results of bug detection in non-linearizable implementations.	b:	max bour	nd on
#operation per process, t: time used (sec.), and s: memory used (GB).			

test		norm	al		simp	le	ро	lynon	nial		norm	nal	simple			polynomial				
test	b	t	s	b	t	s	b	t	s	b	t	s	b	t	s	b	t	s		
algorithm				3 p	oroces	sses							4	proce	esses					
BOWMAN	$\infty$	11	0.64	$\infty$	2	0.1	$\infty$	2	0.3	3	168	12.0	$\infty$	60	0.5	$\infty$	54	0.6		
JAYANTI	14	272	22.8	23	393	25.1	3	72	0.7	3	149	11.9	6	218	16.0	3	98	0.7		
AFEK1	-	-	-	2	242	1.9	2	417	1.8	-	-	-	2	305	2.0	2	506	2.3		
AFEK2	2	50	0.5	4	422	4.3	3	215	1.4	2	163	2.0	4	522	7.0	3	255	2.1		
RIANY	6	285	4.1	9	445	5.4	27	595	2.0	3	172	12.1	6	275	17	24	512	1.9		
algorithm	5 processes 6 processes																			
BOWMAN	1	9	0.4	3	290	18.4	40	575	4.4	1	66	3.8	1	7	0.5	35	507	3.3		
JAYANTI	1	141	0.9	3	253	18.4	3	118	0.7	1	302	4.6	2	590	28.1	3	142	0.7		
AFEK1	-	-	-	2	417	4.0	-	-	-	-	-	-	-	-	-	-	-	-		
AFEK2	1	21	0.4	3	441	18.4	3	298	2.6	1	95	4.2	1	7	0.5	3	326	2.8		
RIANY	-	_	-	-	_	-	23	579	1.8	-	_	-	-	_	-	21	508	2.2		
algorithm				8 I	oroces	sses				10 processes										
BOWMAN	-	-	-	1	288	15.6	33	554	2.7	-	-	-	-	-	-	30	558	2.9		
JAYANTI	-	-	-	1	386	15.6	3	197	0.7	-	-	-	-	-	-	3	267	1.1		
AFEK1	-	-	-	-	-	-	-	-	-	-	-	-	-	_	-	-	-	-		
AFEK2	-	-	-	1	256	15.7	3	402	3.2	-	-	-	-	-	-	3	491	3.6		
RIANY	-	-	-	-	-	-	19	502	2.2	-	-	-	-	-	-	18	586	3.0		

## 7.5.1 Verification Experiments

To address RQ1 and RQ2, we used PAT to verify the correctness of our configurations. We ran three different types of linearizability experiments:

normal. Using PAT's standard linearizability checker with full and buggy-full configurations. simple. Using PAT's standard linearizability checker with simple-only and buggy-simple-only configurations.

polynomial. Using PAT's reachability checker with simple-only and buggy-simple-only configurations, in parallel to the automaton threads that detect bugs.

Furthermore, for each configuration and matching experiment type, we limited the number of operations that each process was allowed to perform. As some algorithms employ infinite data types (e.g. integers), at least in those cases, the bound is mandatory for PAT to terminate. We set a timeout of 10 min. for buggy implementations, and 1 hr. for correct implementations. We repeated each experiment with various bounds until we found the maximal bound for which each experiment terminated in the allotted time.

- ▶ Remark 19. For simple configurations, we checked only (0,1)-simple histories. For full verification, it is required to test all (i,j)-histories. Nevertheless, this observation does not affect the feasibility of the approach, since the tests for  $(i_0,j_0)$  and  $(i_1,j_1)$  simple histories are independent, and can even run on separate machines. Furthermore, symmetry arguments may increase confidence even when checking only (0,1)-simple histories.
- ▶ Remark 20. We also tried to use Cave [21,50] and its extension Poling [45,55], static analysis-based linearizability verifiers. Unfortunately, despite our best efforts, we could not make either tool work for the algorithms we tried to encode. Even for toy correct and

normal simple polynomial normal simple polynomial test b b  $\mathbf{t}$ b  $\mathbf{t}$ b  $\mathbf{t}$  $\mathbf{t}$  $\mathbf{S}$  $\mathbf{S}$ b  $\mathbf{S}$ b t  $\mathbf{S}$  $\mathbf{S}$  $\mathbf{S}$ algorithm 3 processes 4 processes **BOWMAN** 0.70.7 2 47  $\infty$ 3 0.1 $\infty$ 11 0.11 29 0.6 $\infty$ 1341.8  $\infty$ 460 **JAYANTI** AFEK1 113 1.0 15 0.2 1 31 0.3 AFEK2 12 0.22 262719.5 2 2675 7.5 1 269 154 1.9 1 1.5 **RIANY** algorithm 5 processes 6 processes **BOWMAN** 1 158 1.4 1 1210.5 **JAYANTI** AFEK1 AFEK2 RIANY

**Table 2** Results of verification of linearizable implementations. b: max bound on #operation per process, t: time used (sec.), and s: memory used (GB).

incorrect algorithms that operate atomically, Cave reported errors, and Poling returned unexpected responses. Perhaps the snapshot object deviates from the types of data structures that these tools aim to handle. To the best of our knowledge, PAT, Cave, and Poling are the only available tools that verify linearizability automatically, without requiring additional input.

We present the bug-detection results in Table 1, and the verification results in Table 2. For each configuration and linearizability experiment type, we report the maximal bound on the number of operations per process, for which the experiment terminated before the timeout. If the experiment terminated without imposing a bound, we report the value  $\infty$ . Furthermore, for the max bound we found, we report time and space consumption by the corresponding linearizability experiment. As an example, for RIANY buggy-simple-only with 4 processes, when we ran the polynomial linearizability experiment, we found the bug while limiting each process to 24 operations. The execution took 512 sec. and consumed 1.9 GB. Accordingly, in the upper part of Table 1, the cells on the row titled "RIANY" and the columns titled "polynomial; 4 processes" read: b:24, t:512, and s:1.9.

#### 7.5.2 Testing Experiments

To address RQ3, we tested all linearizable and non-linearizable generated histories, applying two methods: our implemented method, and a tool by Lowe [37,41], with a 10 min. timeout. For each configuration and each tool, we report the percentage of tests that successfully terminated within the allotted time. Furthermore, for the terminated executions, we report the median running time and space consumption. Table 3 presents results for linearizable configurations, and Table 4 for non-linearizable configurations. As an example, when we applied our method to linearizable histories of length 500 with 20 processes, 100% of the tests were successful, the median running time was 0.15sec, and the median space consumption was 150MB. Hence, in Table 3, the cells on the rows titled "500:terminated", "500;median time", and "500;median space" with the column titled "20;This paper" read 100%, 0.15, and 150, respectively.

**Table 3** Linearizable simple history testing results. Terminated tests (%), median time used (sec.), and median memory used (MB).

#pro	cesses		j .	8	3	1	1	1	4	17		20	0
len.	mth.	This paper	Lowe	This paper	Lowe								
	term.	100%	100%	100%	100%	100%	100%	100%	84%	100%	52%	100%	32%
200	time	0.02	0.20	0.02	0.22	0.02	0.28	0.02	1.34	0.02	1.11	0.03	2.08
	space	130	336	131	352	131	360	131	456	131	444	132	1228
	term.	100%	100%	100%	100%	100%	100%	100%	80%	100%	48%	100%	16%
500	time	0.04	0.20	0.06	0.22	0.09	0.30	0.12	1.45	0.16	12.57	0.15	0.21
	space	132	216	136	336	140	352	144	492	150	2414	150	346
	term.	100%	100%	100%	100%	100%	100%	100%	72%	100%	44%	100%	16%
1000	time	0.07	0.21	0.14	0.21	0.21	0.33	0.33	1.36	0.40	3.29	0.56	0.85
	space	136	344	146	336	156	352	171	482	182	1620	203	398

**Table 4** Non-linearizable simple history testing results. Terminated tests (%), median time used (sec.), and median memory used (MB).

#pr	ocesses	3	3	4	Į.	5	5	(	3	3	3	1	.0
len.	mth.	This paper	Lowe	This paper	Lowe	This paper	Lowe	This paper	Lowe	This paper	Lowe	This paper	Lowe
	term.	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
50	time	0.06	0.28	0.06	0.32	0.06	0.34	0.06	0.35	0.06	0.65	0.06	1.19
	space	129	336	129	348	129	336	129	344	129	368	129	440
	term.	100%	100%	100%	100%	100%	84%	100%	52%	100%	32%	100%	8%
100	time	0.03	0.48	0.03	1.45	0.03	3.76	0.03	24.61	0.03	61.93	0.03	179.80
	space	129	340	129	508	129	2784	129	17896	129	12996	129	12192
	term.	100%	36%	100%	4%	100%	0%	100%	0%	100%	0%	100%	0%
200	time	0.03	30.78	0.03	5.11	0.03	-	0.03	-	0.03	-	0.03	-
	space	129	20392	129	3216	129	-	129	-	129	-	129	-

## 7.6 Analysis of the Results

Focusing on simple histories is beneficial, as both simple and polynomial outperform the normal linearizability method of PAT for finding bugs. In addition, overall, polynomial performs better than simple (see Table 1). normal found the bug in 14/30 cases, with up to 6 processes. simple succeeded in 3 additional cases with up to 8 processes, with polynomial succeeding in 26/30 cases with up to 10 processes. Importantly, simple allows for larger bounds than normal in 16/17 cases, and the same bound in the remaining case. polynomial allows for larger bounds than simple in 16 cases, and smaller bounds in 5 cases. This indicates that polynomial enables deeper exploration than simple, and thus we conclude that it is more efficient. Both polynomial and simple manage to explore implementations significantly deeper than normal. We also observe that polynomial consumes less space, which is the main bottleneck of model checking, than simple. The peak memory consumption we recorded for polynomial was 4.4GB, whereas the peak we recorded for simple was 25.1GB, and 9/20 executions with more than 10GB. While the peak we recorded for normal was 22.8GB, it scaled much worse than simple and failed to cope with the more challenging configurations.

In Table 2, we see that simple and polynomial enable the verification of BOWMAN with 3 and 4 processes. To the best of our knowledge, this is the first time that this algorithm has been verified to some extent. Model-checking techniques are complete and mainly efficient for

bug detection. Verifying a concurrent algorithm for 4 processes is noteworthy (compare, e.g., to the results of [39]). Yet, excluding these results, although both methods perform better than normal, we did not manage to verify other implementations. We mention that, in some old evaluations we performed, we used a prototype tool we wrote that uses simple histories (but does not employ the automatons of Section 4.1), and managed to verify JAYANTI with 3 processes within 21 sec. (reference hidden for double-blind review). As this deviates from what Table 2 illustrates, we believe that further investigation is required.

Tables 3 and 4 show that our testing technique outperforms [41] by several orders of magnitude, mainly and most importantly, in terms of feasibility. Our tool easily handled all 900 histories, while the competitor failed to cope with challenging configurations, successfully handling only 554/900 histories. We also observe that our technique is scalable. The differences in time and space consumption between extremum values are negligible.

Moreover, we note that our technique is insensitive to the correctness of the tested history. In contrast, our competitor quickly fails over non-linearizable histories. To gain more confidence in this observation, we further generated 25 non-linearizable histories of length 1000 for 20 processes, with a linearizable prefix of length at least 980. Our tool handled all with a median running time of 0.55sec. Note that our competitor failed almost entirely over non-linearizable histories of length 200, with 3-10 processes.

### 8 Related Work

Alur et al. proposed an EXPSPACE-technique for verifying linearizability [5], and Hamza proved EXPSPACE-completeness [29]. Bouajjani et al. proved the undecidability of linearizability of infinite-state systems, and the PSPACE-completeness of linearizability with fixed linearization points [14].

Due to the high complexity of the problem, sound and complete model-checking techniques manage to perform limited verification with up to 3 processes [19, 39, 52]. [39] also verifies a stack implementation for 4 processes, but only by limiting the stack size to two data values. Hsu et al. [33] proposed a bounded model checking technique for hyper-LTL, and used it to rediscover known bugs (see [25]) in the "Snark" dequeue implementation [24].

Static analysis efforts are incomplete, but can work for infinite-state implementations. However, most ask for additional information from the user. The works [3, 6, 13, 50] ask for linearization points, some in a conditional manner. The work [2] asks for linearization policies. The work [47] asks for the specification of sub-operations and relations between them. Cave [21,51] and Poling [55] work without further information. However, as we report in Section 7, we did not manage to work with these tools. Perhaps the snapshot object deviates from the types of data structures that these tools aim to handle.

The way we employ the data independence property resembles Abdulla et al. [1]. They ran automatons in parallel to queue and stack implementations to detect bugs. Their approach is incomplete, but works for infinite-state implementations. However, their automatons detect incorrect sequential histories, in contrast to concurrent histories as we do, and thus their approach requires specifying linearization points. It is rather simple to construct an automaton that detects incorrect sequential snapshot histories, hence their approach can be applied to the snapshot object straightforwardly. But, as linearization points of snapshot implementations are evasive, the benefit of doing so is questionable.

Other works also focused on specific data structures. Bouajanni et al. [15] prove that verification of data-independent queue, stack, register, and mutex implementations is PSPACE-complete for a fixed number of processes, and EXPSPACE-complete for infinitely many

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processes. In [16], Bouajjani et al. extend the latter result to data-independent and projection-closed priority queues. To the best of our knowledge, those techniques have not been implemented or evaluated. Chakraborty et al. [22] identified conditions that are equivalent to the linearizability of data-independent queue implementations, and use them to automatically verify Herlihy and Wing's queue [31]. Abdulla et al. [3] used those conditions and the results of [22] to extend their static analysis technique [2] to verify stack and queue implementations without linearization points.

Wing and Gong considered the problem of testing linearizability, and gave an exponential-time algorithm [53]. Gibbons and Korach proved NP-completeness [28], and further showed that register-histories with k processes can be tested in time  $O(n2^{O(k)} + n \log n)$ . Lowe [41] suggested optimizations for the algorithm of [53]. Horn and Kroening suggested an optimization that applies to set implementations [32]. Emmi and Enea [27] identified a class of data structures for which a polynomial-time testing algorithm exists. This class includes queue, stack, set, and map, but does not include snapshot.

## 9 Conclusion

We proved that a data-independent snapshot algorithm is linearizable if and only if all of its simple histories are linearizable. This gives rise to an optimization for proving/disproving the correctness of snapshot implementations, i.e, examining only simple histories. This optimization can exponentially reduce the number of reachable states to inspect. Moreover, we proved that non-linearizable simple histories are identified by a polynomial-sized automaton. This enables a polynomial-time technique for verifying the linearizability of snapshot implementations, and a linear-time technique for testing the linearizability of snapshot histories. We implemented our techniques, and reported on evaluations that support the efficiency of our methods over existing techniques.

#### **Future Work**

We wonder if the notion of simple histories can be replicated to other data structures. In particular, it would be interesting to investigate whether such an adaptation would admit automata-based verification/testing techniques similar to those we presented for the snapshot object. The automatons presented in [14] seem like a good place to begin in order to define simple histories geared at queues and stacks. Another future direction is to extend our results to multi-writer snapshots, and to implementations that are strongly linearizable [43].

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