2D-Stack:
A scalable lock-free stack design that continuously relaxes semantics for better performance

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Göteborg, 2018
Abstract

In this report, we propose an efficient lock-free concurrent stack design with tunable and tenable relaxed semantics to allow for better performance. The design is materialized by a shared memory distributed stack design, that allow for a continuous monotonic trade of weaker semantics for better throughput performance. Concurrent stacks have an inherent scalability bottleneck due to their single access point for both push and pop operations.

Elimination and semantics relaxation have been proposed in the literature to address this problem. Semantic relaxation has the potential and flexibility to reach monotonically very high throughput. Previous solutions could not fully leverage this potential. We propose a new two-dimensional design that can achieve this by exploiting disjoint access parallelism in one dimension and locality in the other. This is achieved through distributing the stack in form of sub-stacks that are accessed independently in parallel. Load balancing is used to keep a balanced number of operations on individual sub-stacks.

We also provide tight relaxation bounds for the behaviour of our algorithm. We compare experimentally to previous work, with respect to throughput and relaxed behaviour observed, on different relaxation and concurrency settings. The results show that our algorithm significantly outperform all other algorithms in terms of performance, while maintaining better quality in contrast to other designs with relaxed semantics.

Keywords — Stack, Lock-free, Relaxed Semantics, Concurrency, Data Structures, Weak Consistency, Distributed Algorithms.
1 Introduction

Stacks entered the computer science literature in 1946, when Alan M. Turing used the terms “bury” and “unbury” as a means of calling and returning from subroutines. Stacks are linear data structures or more abstractly sequential collections of ordered items with two principle operations: Push, which adds an item and pop, which removes an item. The Push and Pop operations occur at a single point of the structure, referred to as the top or head of the stack. Stack operations follow the Last In First Out (LIFO) semantics. Concurrent stacks, like any other concurrent data structure, require synchronization to guarantee the behavior that is legal with respect to their exact sequential specifications. However, synchronization may incur high performance overhead with increase in the number of threads. In the case of a stack, the overhead can be attributed to the joint access point at the stack top leading to contention and a scalability bottleneck. Synchronization is vital to achieving correctness and cannot be eliminated [5], whereas this is true, synchronization and scalability conflict in form of contention. To reduce contention and improve on scalability, synchronization points need to be distributed by creating disjoint access points. Disjoint access techniques for stacks like: elimination [1, 12, 17], combining [18] and dynamic elimination-combining [7] have been proposed in the literature. Such techniques allow threads to complete their operations without necessarily accessing the top of the stack. These techniques however depend on the existence of other concurrent operations being present, introducing a waiting time between dependant operations. For example Push waiting for Pop elimination and Push waiting for Push combining.

To further improve performance scalability of concurrent data structures, recent research has focused on expanding the set of legal behaviours, including; weakening consistency and semantic relaxation for providing trade-offs between scalability and linearizability guarantees. Computability of relaxed data-structures [16] together with their relaxed semantics definitions including; k-Out-of-Order, k-Lateness and k-Stuttering have been proposed in the literature as interesting relaxation models to consider [13, 20].

Distributing parts and hence access of the data-structure [11, 15, 21], has come out as a frequent technique used to implement relaxation. A given data-structure is split into multiple sub-structures with independent access points to improve on disjoint access parallelism. Operations are distributed over the sub-structures using different scheduling techniques; thread binding [21], random access [15], load-balancing [11], round robin and a combination of others. Various relaxed data-structures have been proposed in the literature, most use one dimension relaxation exploiting disjoint access parallelism or locality. Disjoint access is achieved through creating extra access points, whereas locality is achieved by controlling the number of threads that share a given access point.

In this report, we aim to leverage the semantics relaxation through exploiting disjoint access parallelism and locality. Locality can be obtained by letting a thread work on the same access point for some time in isolation. Previous works have used thread to sub-structure bidding to exploit locality. However, to maintain LIFO accuracy bounds and differ from pool semantics [19, 10, 1], a mechanism that synchronizes the thread local works or limits the amount of the local work must be introduced. This might turn out to be the performance bottleneck as one increases the degree of concurrency [10]. We introduce an algorithm (2D-stack) that enables disjoint access parallelism and exploits the locality within strict deterministic accuracy bounds in an efficient way, avoiding expensive work sharing mechanisms. This would not only increase the performance for a given configuration but also give one the capability to monotonically trade the accuracy for better performance. This is achieved through a distributed stack, composed of multiple sub-stacks. Each sub-stack independently accessed through a pointer pointing to the topmost item of the given sub-stack. We also implement three other distributed stack designs based on known basic scheduling techniques, including Random Single Choice (Random), Random Choice of Two (Random-c2), Round-Robin (k-robin). This is to help us have a detailed comparison of stack semantic relaxation, since such designs have not been proposed with relaxed semantics before. Our 2D-stack design exhibits a two dimension scheduling technique (load balancing), exploiting disjoint access parallelism in one dimension and locality in the other. 2D-stack significantly outperforms previous stack implementations including the extra
three implemented stack designs as observed in the experimental evaluation Section 7.

The report is structured as follows. In Section 2 we discuss literature related to this work. We present the implementations in Section 3 and prove correctness in Section 4. A step complexity analysis is discussed in Section 5. We select optimization parameters in Section 6 and use them for experimental evaluation presented in Section 7. We then conclude in Section 8.

2 Related Work

Concurrent stacks are inherently sequential due to their single point access bottleneck. In the quest to improve performance scalability, disjoint access strategies have been proposed for designing concurrent stacks including; elimination trees [1, 17], combining funnels [18] and elimination back-off [7, 12]. Elimination back-off implements a collision array in which pop operations try to collide and cancel with concurrent push operations to reduce joint access on top of the stack. Such operation pairs create disjoint collisions that are executed in parallel with operations accessing the main stack implementation. As an extended back-off strategy, it reduces joint access to the main stack by canceling out paired operations and completing their execution on the collision array. However, the performance benefits flatten out fast as the number of threads increases to a certain threshold. Elimination back-off mostly benefits symmetric workloads in which the numbers of push and pop operations are roughly equal, its performance deteriorates when workloads are asymmetric.

Recently, semantic relaxation has been proposed for data-structures that provide trade-offs between scalability and linearizability guarantees. Relaxation techniques introduce an acceptable error within the legal strict semantics of a given data-structure, i.e. the pop operation of a relaxed stack is allowed to return any of the $k$ topmost items of the stack. To quantify this error, relaxed semantic definitions including; $k$-Out-of-Order, $k$-Stuttering and $k$-Lateness have been introduced [13, 20]. Based on these definitions, new designs have been proposed for some fundamental data structures to introduce relaxation. A $k$-Out-of-Order stack has been proposed in [13, 2], referred to as Segmented ($k$-segment) henceforth. It is composed of a linked list of memory segments whose size is defined by $k$ number of indexes. The stack items can only be accessed through the topmost segment, where an operation pushes or pops an item from any $k$ indexes. A Push operation adds a new segment if top segment is full whereas a Pop removes a segment if it is empty and not the last segment. A Push operation tries to push an item onto an empty slot in the top segment, adding a new segment if the segment is full. A Pop operation tries to remove an item from the top segment, removing segment if empty and is not the only segment on the stack. Operations perform a linear search for an empty (Push) or filled (Pop) index, starting with randomly index in the topmost segment. Relaxation is controlled through the width dimension with the segment size increasing with increase in of $k$. Increasing $k$ improves on disjoint access and reduces contention up-to a given threshold. This is because as $k$ increases to infinity, at some point the gains from the reduced contention diminishes whereas the cost for traversing memory in search of an index increases. This is coupled with accuracy loss proportional to increase in $k$. Also for small $k$ numbers, there is high cost of operation synchronization when trying to remove or add a segment. These performance characteristics of the proposed design, limit scaling and the performance gains of the algorithm with increase in relaxation.

Other relaxed data-structures proposed include, priority queues [4, 15, 21] and shared memory distributed FIFO queues [11].

3 Relaxed Stack Design Description

In this section, we describe our 2D-Stack two dimensional design plus other three related distributed stack designs that we implement for the sake of a detailed study. We follow the same sub-stack design with different thread scheduling techniques. An array of pointers (stack-array) is used to access individual sub-stacks. Each sub-stack is independently accessed through its topmost item
pointer at a given stack-array index. Operations on each sub-stack follow the lock-free Treiber stack
design [8].

The three extra scheduling techniques lead to different stack algorithms that reveal different
performance and accuracy characteristics. Random and Random-c2, are simple randomized stack
algorithms, they use the width dimension to distribute operations by randomly selecting a given
sub-stack to operate on. Random-c2 increases accuracy by employing the random choice of two
technique. Our third algorithm k-robin uses the width dimension to distribute operations following
a strict round robin sub-stack selection.

3.1 2D-Stack

2D-Stack algorithm uses three parameters to tune its performance: width, depth and shift which
form a count based bidirectional operational region (window) in which an operation can occur.
Number of sub-stacks is defined by the width whereas depth defines the maximum number of items
acceptable for a single sub-stack per window. We implement a global counter (Global) that limits
the depth, by defining the maximum and minimum number of items per sub-stack for a given active
window. The window and Global give us the liberty to optimize for both accuracy and throughput
within tightly defined accuracy bounds. A given thread randomly selects a sub-stack to operate
on, tries to keep on the same sub-stack for as long there is no contention and without violating
the Global restrictions. If contention is detected on a given sub-stack, the thread randomly selects
another sub-stack to reduce on contention. This allows threads to optimistically exploit locality
without thread to sub-stack bidding.

The algorithm operations are depicted in Algorithm 1. 2D-stack is a shared memory distributed
stack, composed of multiple lock-free sub-stacks. An individual sub-stack is implemented using
a linked list whose operations follow the Treiber stack design [8]. Each sub-stack has a unique
descriptor (line 1 to 4) that keeps track of the sub-stack information including: pointer to the
topmost item and item-counter. A descriptor has a dedicated memory location accessed through an
array (stack-array). Using a CAE\(^1\) instruction we can update the descriptor contents in one atomic
step to maintain correctness (line 15 and 27 for Push and Pop respectively).

To perform an operation, a thread searches for a sub-stack based on the Global (GetIndex). A
thread selects a sub-stack, then, compares the sub-stack item-count with the Global (line 61 or 65).
The thread can then proceed on the selected sub-stack only if the comparison evaluates to true (line
46 or 48). Otherwise the thread has to search for another sub-stack. For each operation, the thread
starts from the previously known sub-stack on which it succeeded (line 44). First the thread tries
given number of random hops (line 50), then switches to round robin until a valid sub-stack is
found, or the thread updates the Global, after failing on all sub-stacks (line 64 or 68).

The Global is updated in relation to depth. If the thread detects contention on a sub-stack, a
random hop to another sub-stack is performed (line 18 or 30). This is to reduce possible contention
on consecutive sub-stacks that might arise from round robin hops. It also introduces our concept of
optimistic locality. A thread can operate on given sub-stack for as long no contention is detected. A
CAE fail signals the presence of another thread operating on the same sub-stack. To avoid further
contention, the thread that has failed leaves the successful thread to take over the sub-stack.

During the search, the thread validates each sub-stack item-count against the Global. The item-
count must be less than Global for Push or greater than the difference between Global and depth
for Pop (line 45 or 47). If the item-count is zero, then the sub-stack is empty. If no valid sub-stack
is found, the Global is updated atomically (line 64 or 68). Push adds whereas Pop subtracts a value
(shift) (line 62 or 66), shift must be less than or equal to depth. Then the search is restarted with
a fresh search count. If a valid sub-stack is found, the thread tries to operate on it, on success the
sub-stack descriptor is updated (line 15 or 27) otherwise another sub-stack is searched for, starting
from a random index (line 18 or 30).

\(^1\)Compare and Exchange (CAE) atomically compares 16 bytes of memory content and exchanges it with new
content on success.
A successful *Push* increments whereas a *Push* decrements the item-counter by one. Also the topmost item pointer is updated. At this point, a *Push* adds an item whereas a *Pop* returns an item for a non empty *sub-stack* or NULL for empty. An empty *sub-stack* is represented by a NULL item pointer within the *descriptor*. As an optimization strategy, the *thread* keeps track of the *Global* for every hop during the search process, restarting for every *Global* change detected. Keeping track of the *Global* prevents the *thread* from doing useless search with stale *Global* information. Consider a *Push* *thread* that reads *Global* just before it is incremented by a preceding *Push* *thread*. The succeeding *thread* will have to check all *sub-stacks* searching for non full *sub-stack* before proceeding to access the updated *Global*. Note that, keeping track of the *Global*, has no added cost apart from the constant one cache miss while accessing an updated *Global*.

### Algorithm 1: 2D-Stack

```c
1 Struct Descriptor 38 Function GetIndex(Op, Index)
2 | item; 39 IndexSearch = 0; PGlo = Glo; Random = 0;
3 | count; unsigned long 40 while true do
4 | version; unsigned long 41 if Index ≥ ArraySize then
5 Struct Global 42 | Index = 0;
6 | count; unsigned long 43 end
7 | version; unsigned long 44 Des = Array[Index]; >> Read descriptor;
8 Function Push(NewItem) 45 if Op == push ∧ Des.count < Glo.count then
9 | while true do 46 return {Des, Index};
10 | {Des, Index} = GetIndex(push, Index); 47 else if Op == pop ∧ (Des.count ≥ (Glo.count - depth) ∨ Des.count == 0) then
11 | NewItem.next = Des.item; 48 return {Des, Index};
12 | NDes.item = NewItem; 49 else if PGlo == Glo then
13 | NDes.count = Des.count + 1; 50 if Random < 2 then
14 | NDes.version = Des.version + 1; 51 | Index = RandomIndex();
15 | if CAE(Array[Index], Des, NDes) then 52 Random += 1;
16 | return 1; 53 else 54 Index += 1;
17 | else 55 end
18 | Index = RandomIndex(); 56 end
19 | end 57 else
20 | end 58 else
21 Function Pop() 59 if IndexSearch == ArraySize then
22 | while true do 60 IndexSearch = 0;
23 | {Des, Index} = GetIndex(pop, Index); 61 if Op == push ∧ PGlo == Glo then
24 | if Des.item != NULL then 62 NGlo.count = PGlo.count + ShiftUp;
25 | NDes.item = Des.item.next; 63 NGlo.version = PGlo.version + 1;
26 | NDes.count = Des.count - 1; 64 CAE(Glo, PGlo, NGlo);
27 | NDes.version = Des.version + 1; 65 else if Op == pop ∧ PGlo == Glo ∧ (Glo.count - depth) > 0 then
28 | if CAE(Array[Index], Des, NDes) then 66 NGlo.count = PGlo.count - ShiftDown;
29 | return Des.item; 67 NGlo.version = PGlo.version + 1;
30 | end 68 CAE(Glo, PGlo, NGlo);
31 | else 69 end
32 | Index = RandomIndex(); 70 end
33 | end 71 else if Random ≥ 2 then
34 | return Null; 72 IndexSearch += 1;
35 | end 73 end
36 ▷ Des stands for descriptor; 74 end
37 ▷ Glo stands for Global;
```

### 3.2 Other Shared Memory Distributed Stack Designs

In this section, we present other distributed stack designs based on known basic scheduling techniques. They are briefly described to give the reader an implementation overview for a better performance comparison with the 2D-stack.
3.2.1 Round-Robin
This algorithm uses two parameters to tune its performance: number of threads and number of sub-stacks. Unlike Random and Random-c2 algorithms, k-robin provides a deterministic accuracy bound, linearizable with respect to k-Out-of-Order stack semantics. The algorithm distributes operation following a strict round robin fashion without skipping a sub-stack. Each thread has two local independent counters, a Pop operation counter and a Push operation counter. A thread tries to operate on a sub-stack indicated by a given operation counter, if successful, it increases the respective counter for the next operation. Otherwise it keeps trying on the same sub-stack until it succeeds.

3.2.2 Random Single Choice
This is the most basic algorithm designed on top of the sub-stack design. It takes a single parameter: number of sub-stacks (width). For both Pop and Push operations, a thread selects a sub-stack uniformly at random to perform its operation. Once the sub-stack is selected, the respective operation follows the Treiber stack design.

3.2.3 Random Choice of Two
In the bid to improve on accuracy, Random Single Choice is extended to Random. Random-c2 design is based on the principle of power of random two choices[14], also similar to MultiQueues [6] and Power of choice of two [3]. Like in Random the number of sub-stacks remains as the only parameter to select for tuning. The algorithm is depicted in Algorithm 2. Each pushed element is tagged with a time-stamp generated using a globally consistent clock (line 5). Time-stamps provide for a logical global ordering of elements. A Pop operation randomly selects two sub-stacks and proceeds to pop from the sub-stack whose element has the highest time-stamp (line 25). A Push operation, randomly selects a sub-stack and proceeds to push the element onto it (line 4).

Algorithm 2: Random Choice of Two

```
Function PushItem (*NewItem)
1  *Item;
2  while true do
3    index = RandomIndex(); Item = StackArray[index].item;
4    NewItem→next = Item; NewItem→tag = Timestamp;
5    if CAS(StackArray[index].item, Item, NewItem) then
6      return 1;
7    end
8  end
9
Function PopItem ()
10 *Item; *NewItem; tag1 = 0; tag2 = 0;
11 while true do
12  index1 = RandomIndex();
13  while StackArraySize > 1 do
14    index2 = RandomIndex();
15    if index1 != index2 then
16      tag1 = Item1→tag; tag2 = Item2→tag;
17      if tag1 > tag2 then
18        index = index1; break ;
19      else
20        index = index2; break ;
21      end
22    end
23  end
24  Item = StackArray[index].item;
25  if Item != NULL then
26    NewItem = Item→next;
27    if CAS(StackArray[index].item, Item, NewItem) then
28      return Item;
29    end
30  else
31    return 1;
32  end
33
```

4 Correctness

In this section, we prove the correctness of our algorithms. We examine and prove linearizability and lock-freedom for both k-robin and 2D-stack. We do not consider Random and Random-c2 in this section, since the k would be unbounded (proportional to the maximum number of items in the stack) for these two algorithms.

To begin with, we introduce the linearization points of Push and Pop operations for both stack designs; the linearization points are the same points (same program lines) that the original Treiber’s Stack implementation had as linearization points. For 2D-stack, Pop linearizes either by returning NULL (at line 33) or with a successful CAE at line 27. Push linearizes with a successful CAE at line 15. For k-robin, Pop linearizes either by returning NULL or with a successful CAS that pops an item by modifying the top pointer of a sub-stack. Push linearizes with a successful CAS that modifies the top pointer of a sub-stack.

We prove the linearizability of 2D-stack and k-robin with respect to the sequential semantics of k-Out-of-Order stack [13], which provides a relaxed version of the LIFO semantics. Relaxation can be applied method-wise and it is applied only to Pop operations in k-Out-of-Order stack, i.e. a Pop pops one of the topmost k items. Push operations add the item to the top of the stack.

4.1 2D-Stack

Firstly, we require some notation. window defines the active region in which the operations are allowed to proceed (line 45 and 47 for Push and Pop respectively). The window is shifted by the parameter shift, 1 \( \leq \text{shift} \leq \text{depth} \). A window \( i \) (\( W^\text{up}_i \)) has an upper bound (\( W^\text{up}_{i+1} \)) and a lower bound (\( W^\text{down}_i \)), that are defined by \( W^\text{up}_i = \text{depth} + (i \times \text{shift}) \) and \( W^\text{down}_i = i \times \text{shift} \), respectively. And, a window is active if \( W^\text{up}_i = \text{Global} \). The width parameter describes the number of sub-stacks. The number of items of the sub-stack \( j \) is denoted by \( N_j \), 1 \( \leq j \leq \text{width} \). To recall, the top pointer, the version number and \( N_j \) are embedded into the descriptor of sub-stack \( j \) and all can be modified atomically with a CAE.

Lemma 1 Given that \( \text{Global} = \text{depth} + \text{shift} \times i \), it is impossible to observe a state(S) such that \( N_j > W^\text{up}_{i+1} \) (or \( N_j < W^\text{down}_{i-1} \)), where 1 \( \leq j \leq \text{width} \).

Proof: Recall that \( \text{Global} = W^\text{up}_i \) defines the active window where the operations are allowed to start. Though, they might linearize while the active window is set to an adjacent window (\( \text{Global} = W^\text{up}_{i-1} \) or \( \text{Global} = W^\text{up}_{i+1} \)). We can not observe such a state in the initialization, therefore there should exist a point in time that this state \( (S) \) is observed for the first time, with \( \text{Global} = \text{depth} + \text{shift} \times i \) and \( N_j > W^\text{up}_{i+1} \) (or \( N_j < W^\text{down}_{i-1} \)), but we do not consider this symmetric case in the proof since it can be covered with the same arguments as \( N_j > W^\text{up}_{i+1} \). Now, we show that this is impossible by considering the interleaving of operations.

Without loss of generality, assume thread 1 (\( T_1 \)) has set \( \text{Global} = \text{depth} + \text{shift} \times i \) with the CAE (at line 64 or 68) at time \( t_{11} \). To do this, \( T_1 \) should have observed either \( \text{Global} = \text{depth} + \text{shift} \times (i-1) \) and then \( N_j = W^\text{up}_{i-1} \) or \( \text{Global} = \text{depth} + \text{shift} \times (i+1) \) and then \( N_j = W^\text{down}_{i+1} \). Let this observation of \( \text{Global} \) (at line 39) happen at time \( t_1 \). Consider the last successful push operation at sub-stack \( j \) before the state \( S \) is observed for the first time (we do not consider Pop operations as they can only decrease \( N_j \) to a value that is less than \( W^\text{up}_{i+1} \), this case will be covered by the first item below). Assume thread 0 (\( T_0 \)) sets \( N_j \) to \( N_j > W^\text{up}_{i+1} \) in this push operation. In this operation, \( T_0 \) should observe \( N_j > W^\text{up}_{i+1} \) (at line 44) and \( \text{Global} > W^\text{up}_{i+1} \) (at line 45). Let line 45 is executed (atomic read) at time \( t_0 \). And the linearization of the operation happens at \( t_{01} > t_0 \) with CAE (at line 15).

- If \( t_{01} < t_1 \), the concerned state(S) can not be observed since, \( \text{Global} \) can not be changed (to \( \text{depth} + \text{shift} \times i \)) after \( N_j > W^\text{up}_{i+1} \) is observed.

- Else if \( t_{11} < t_0 \), the concerned state(S) can not be observed since, the push operation can not proceed after observing \( \text{Global} \) (at line 45) with such \( N_j \).
Similarly, we can deduce that at time $t$, the maximum number of items, that are pushed to sub-stack respectively, on Lemma 2, we can deduce that at time $t$ this implies $Global$ has been modified since it had read by $T_1$ (at line 39), thus $CAE$ (at line 64 or 68) would fail, at least based on the version number.

Hence, the lemma.

**Lemma 2** At all times, there exist an $i$ such that $\forall j, 1 \leq j \leq width: W_i^{down} \leq N_j \leq W_i^{up}$.

**Proof:** Informally, the lemma states that the size of the sub-stacks spans to at most two consecutive windows. Assume that the statement is not true, then there should exist a pair of sub-stacks (let $k$ and $j$) at some point in time such that $\exists i, N_j > W_i^{up}$ and $N_k < W_i^{down}$. One can not observe such $N_j$ and $N_k$ at the initialization. Then, there should exist a time $t$ that this is observed for the first time. Consider the last push operation at sub-stack $j$ and last pop operation at sub-stack $k$ that linearize before or at the time $t$.

Assume thread 0 ($T_0$) sets $N_j$ and thread 1 ($T_1$) sets $N_k$. To do this, $T_0$ should observe $N_j \geq W_i^{up}$ (at line 44) and $Global > W_i^{up}$ (at line 45), let line 45 (atomic read of $Global$) is executed at $t_0$.

And, the linearization of the Push operation occurs at $t_0 > t$ with the CAE (at line 15). Similarly, for the Pop operation of $T_1$, let line 47 is executed at $t_1$ and the observed value should be $Global \leq W_i^{down}$. And, let the Pop operation linearize at time $t_1 < t$ with the CAE (at line 27). Now, we consider the possible interleavings.

- If $t_0 < t_1$ (or the symmetric $t_1 < t_0$ for which we do not repeat the arguments), then for $T_1$ to proceed and pop an item from sub-stack $k$, it is required that $Global \leq W_i^{down}$ (at line 47). Based on Lemma 1, this is impossible when $N_j > W_i^{up}$.

- Else if $t_1 > t_0$, then $T_0$ can not succeed in the CAE (at line 15) because this implies that $N_j$ has modified (the difference between the value of $Global$ that is observed by $T_0$ and then by $T_1$ implies this) since $T_0$ have read the descriptor (at line 44). At least, the version number would have changed since then, thus leading to a failed CAE (at line 15).

- Else if $t_0 > t_1$, the argument above holds for $T_1$ too, so $T_1$ should fail at the CAE (at line 27).

Such $N_j$ and $N_k$ pair can not co-exist at any time, hence, the lemma.

**Theorem 3** 2D-stack algorithm is linearizable with respect to k-Out-of-Order stack semantics, where $k = (2(\text{shift} + \text{depth})\text{(width} - 1))$.

**Proof:** Consider the linearization points of the Push and the Pop operations that insert and remove the item $e$ into and from a sub-stack (let sub-stack $j$). Let $t_e^{push}$ and $t_e^{pop}$ denote these points respectively, $t_e^{pop} > t_e^{push}$. Now, we bound the maximum number of items, that are pushed after $t_e^{push}$ and are not popped before $t_e^{pop}$, to obtain $k$. Let $N_j$ become $x$ with the linearization of the push operation that inserts item $e$. In other words, item $e$ is the $x$th item from the bottom of the sub-stack. Consider a window $i$ such that: $W_i^{down} \leq x \leq W_i^{up}$.

Lemma 2 states that the sizes of the sub-stacks should reside in a bounded region. Relying on Lemma 2, we can deduce that at time $t_e^{push}$, the following holds: $\forall i : N_i \geq W_i^{down} - shift$. Similarly, we can deduce that at time $t_e^{pop}$, the following holds: $\forall i : N_i \leq W_i^{up} + shift$. Therefore, the maximum number of items, that are pushed to sub-stack $i$ ($i \neq j$) after $t_e^{push}$ and are not popped before $t_e^{pop}$ is at most $W_i^{up} + shift - (W_i^{down} - shift) = depth + 2shift$. We know that this number is zero for sub-stack $j$ (the sub-stack that $e$ is inserted) and we have width $- 1$ other sub-stacks. So, there can be at most $(depth + 2shift)(\text{width} - 1)$ items that are pushed after $t_e^{push}$ and are not popped before $t_e^{pop}$. Hence, the theorem.
4.2 Round-Robin

Theorem 4 k-robin is linearizable with respect to k-Out-of-Order stack semantics, where \( k = (2P − 1)(\text{width} − 1) \). \( P \) stands for the total number of concurrent threads and width denotes the number of sub-stacks.

Proof: Consider the linearization points of Push and Pop operations that respectively insert and remove the item \( e \) into and from a sub-stack (let sub-stack 0). Let \( t^\text{push}_e \) and \( t^\text{pop}_e \) denote these points, respectively. Now, we bound the maximum number of items, that are pushed after \( t^\text{push}_e \) and are not popped before \( t^\text{pop}_e \), to obtain \( k \). We denote the number items that are pushed to (popped from) sub-stack \( i \) by thread \( j \) in the time interval \([t^\text{push}_e, t^\text{pop}_e]\), with \( \text{push}^j_i \) (\( \text{pop}^j_i \)).

Observe that each thread applies its operations in round robin fashion without skipping any index. If the previous successful Pop had occurred at sub-stack \( i \), the next Pop occurs at sub-stack \( i + 1 \)\( \text{mod} \text{width} \). The same applies for the push operations.

Without loss of generality, assume that thread 0 has inserted item \( e \) to sub-stack 0. This implies that \( \forall i, \text{width} − 1 ≥ i > 0, \text{push}^0_i ≥ \text{push}^0_i \). Now, take another thread \( j \), we have \( \forall i : \text{width} − 1 ≥ i > 0, \text{push}^j_i ≥ \text{push}^j_i − 1 \). Informally, another thread can increase the number of items on any other sub-stack by at most one more compared to the number number of items that pushes on sub-stack 0.

For the pop operations, we have the same relation for all threads: \( \forall i, \text{width} ≥ i > 0, \text{pop}^j_i ≥ \text{pop}^j_i + 1 \). Informally, a thread can pop at most 1 item less from any other sub-stack compared to the number that it pops from sub-stack 0. As the interval \([t^\text{push}_e, t^\text{pop}_e]\) starts with the push and ends with the pop of item \( e \) at sub-stack 0, we have \( \sum_{j=0}^{T-1} \text{push}^j_0 = \sum_{j=0}^{T-1} \text{pop}^j_0 = Y \).

Summing over all threads and sub-stacks other than sub-stack 0, we get at most \( (Y + T − 1)(\text{width} − 1) \) Push operations in the interval \([t^\text{push}_e, t^\text{pop}_e]\). Summing over all threads and sub-stacks other than sub-stack 0, we get at least \( (Y − T)(\text{width} − 1) \) Pop operations. Which leads to the theorem: \( k ≤ ((Y + T − 1) − (Y − T))(\text{width} − 1) = (2T − 1)(\text{width} − 1) \).

4.3 Lock-freedom

All algorithm designs presented in this study are lock-free. This follows from the properties of the lock-free Treiber Stack design except for 2D-Stack. An operation can fail on CAE only if there is another successful operation ensuring the system progress. For the 2D-Stack, one should additionally consider if there is a possibility of live-lock due to the update of Global that determines the active window. The Global can be updated repeatedly back and forth if two opposite operations follow each other on an empty or full active window. For example, a Pop operation might read an empty window and update Global leading to a full window, but before it performs its operation, a subsequent Push reads the full window and updates Global leading to an empty window. This process can continue forever leading to a system live lock. This can however be avoided by setting the shift parameter to less than depth. With this setting, a Global update can never lead to a full or empty window unless if the stack is empty. Therefore, a thread would eventually proceed and reach to the CAE at the end of a Push or a Pop that can only fail due to another concurrent successful operation.

5 Complexity Analysis

In this section, we analyze the 2D-stack expected step complexity of a sequential process where a single thread applies the sequence of operations. The type of an operation in the sequence is determined with an independent coin toss with a fixed probability, where \( p \) denotes the probability of a Push operation. With distributed access points, it is possible to make multiple hops on different access points before finding an appropriate point to complete a given operation.
Global regulates the size of the sub-stacks. Recall that the number of sub-stacks is denoted by width and the size of sub-stack \(i\) by \(N_i\). \(Push\) and \(Pop\) operations are allowed to occur at sub-stack \(i\), if \(N_i \in [\text{Global} - \text{depth}, \text{Global} - 1]\) and \(N_i \in [\text{Global} - \text{depth} + 1, \text{Global}]\), respectively. This basically means that, at any time, the size of a sub-stack can only vary in the vicinity of \(\text{Global}\), more precisely: \(\forall i, (\text{Global} - \text{depth}) \leq N_i \leq \text{Global}\). To recall, this interval is valid for the sequential process. We refer to this interval as the active region.

We introduce random variables \(N_i^{active} = N_i - (\text{Global} - \text{depth})\), \(N_i^{active} \in [0, \text{depth}]\) that provides the number of items in the active region of the sub-stack \(i\) and the random variable \(N^{active} = \sum_{i=1}^N N_i^{active}\) provides the total number of items in the window.

As mentioned before the 2D-stack tries to exploit locality, thus, a \(thread\) starts an operation with a query on the sub-stack where the last successful operation occurred. This means that the \(thread\) hops iff \(N_i^{active} = 0\) or \(N_i^{active} = \text{depth}\) respectively for a \(Pop\) or a \(Push\) operation. Therefore, the number of sub-stacks, whose active regions are full, is given by \([(N^{active}/\text{depth})]\) at a given time, because the \(thread\) does not leave a sub-stack until its active region gets either full or empty. If the \(thread\) hops a sub-stack, then a new sub-stack is selected uniformly at random from the remaining set of sub-stacks. If none of the sub-stacks fulfills the condition (which implies that \(N_i^{active} = 0\) at a \(Pop\) or \(N_i^{active} = \text{depth} \times \text{width}\) at a \(Push\)), then the window shifts based on a given shift parameter. (i.e. for a \(Push\) operation \(\text{Global} = \text{Global} + \text{shift up}\) and for a \(Pop\) operation \(\text{Global} = \text{Global} - \text{shift down}\), where \(1 \leq \text{shift down} \leq \text{depth}\) ). One can observe that the value of \(N_i^{active}\) before an operation defines the expected number of hops and the slide of the window.

To compute the expected step complexity of an operation that occurs at a random time, we model the random variation process around the \(Global\) with a Markov chain, where the sequence of \(Push\) and \(Pop\) operations lead to the state transitions. As a remark, we consider the performance of the sub-stacks mostly when they are non-empty, since \(Pop\) (\(\text{NULL}\)) and \(Push\) would have no hops in this case. The Markov chain is strongly related to \(N^{active}\). It is composed of \(K + 1\) states \(S_0, S_1, \ldots, S_K\), where \(K = \text{depth} \times \text{width}\). For all \(i \in [0, K + 1]\), the operation is in state \(S_i\) iff \(N_i^{active} = i\). For all \((i, j) \in [0, K + 1]^2\), \(\mathbb{P}(S_i \to S_j)\) denotes the state transition probability, that is given by the following function, where \(p\) denotes the probability of a \(Push\):

\[
\begin{align*}
\mathbb{P}(S_i \to S_{i+1}) &= p, & \text{if } 0 < i < K \\
\mathbb{P}(S_i \to S_{i-1}) &= 1 - p, & \text{if } 0 < i < K \\
\mathbb{P}(S_i \to S_{K-(\text{shift} \times \text{width} - 1)}) &= p, & \text{if } i = K \\
\mathbb{P}(S_i \to S_{(\text{shift} \times \text{width} - 1)}) &= 1 - p, & \text{if } i = 0 \\
\mathbb{P}(S_i \to S_j) &= 0, & \text{otherwise}
\end{align*}
\]

The stationary distribution (denoted by the vector \(\pi = (\pi_i)_{i \in [0, K]}\)) exists for the Markov chain (let \(\mathbb{P}(S_i \to S_j) = \epsilon, i \in \{\text{depth}, K - \text{depth}\}\), for some \(Pop\) returning \(\text{NULL}\)), since the chain is aperiodic and irreducible. The left eigenvector of the transition matrix with eigenvalue 1 provides the unique stationary distribution.

**Lemma 5** For the Markov chain that is initialized with \(p = 1/2\) and \(\text{shift}\), where \(l = \text{shift} \times \text{width} - 1\), the stationary distribution is given by the vector \(\pi^l = (\pi^l_0, \pi^l_1, \ldots, \pi^l_K)\), assuming \(K - l \geq l\) (for \(l > K - l\), one can obtain the vector from the symmetry \(\pi^l_j = \pi^{K-l}_j\)): (i) \(\pi^l_i = \frac{i+1}{(i+1)(K+l-1)}\), if \(i < l\); (ii) \(\pi^l_i = \frac{i+1}{(i+1)(K+l-1)}\), if \(l \leq i \leq K - l\); (iii) \(\pi^l_i = \frac{K-i+1}{(i+1)(K+l-1)}\), if \(i > K - l\).

**Proof:** We have stated that the stationary distribution exist since the chain is aperiodic and irreducible for all \(p\) and \(\text{shift}\). Let \((M_{i,j})_{(i,j) \in [0,K]^2}\) denotes the transition matrix for \(p = 1/2\) and \(\text{shift}\). The stationary distribution vector \(\pi^l\) fulfills, \(\pi^l M = \pi^l\), that provides the following system of linear equations: (i) \(2\pi^l_0 = \pi^l_1\); (ii) \(2\pi^l_K = \pi^l_{K-1}\); (iii) \(2\pi^l_i = \pi^l_{i-1} + \pi^l_{i+1}\); (iv) \(2\pi^l_i = \pi^l_{i-1} + \pi^l_{i+1} + \pi^l_K\); (v) \(2\pi^l_{l-K} = \pi^l_{l-1} + \pi^l_{l+1} + \pi^l_K\).

In case, \(l = K - l\), then (iv) and (v) are replaced with \(2\pi^l_{l-K} = \pi^l_{l-1} + \pi^l_{l+1} + \pi^l_K\).
The stationary distribution is unique thus for any $\pi^l_0$, $\pi^l$ spans the solution space. We know that $\sum_{i=0}^{K} \pi^l_i = 1$, starting from $\pi^l_0 = 1$, we obtain and normalize each item by the sum.

An operation starts with the search of an available sub-stack. This search contains at least a single query at the sub-stack where the last success occurred, therefore we define the rest of the hops as the extra hops (denoted by Hop, and they can be at most width). In addition, the operation might include the slide of the window, as an extra step, denoted by Glo. We denote the number of extra steps with $\text{Extra} = \text{Hop} + \text{Glo}$. With the linearity of expectation, we obtain $\mathbb{E}(\text{Extra}) = \mathbb{E}(\text{Hop}) + \mathbb{E}(\text{Glo})$. Relying on the law of total expectation, we obtain: (i) $\mathbb{E}(\text{Hop}) = \sum_{i=0}^{K} \sum_{\text{op} \in \{\text{pop, push}\}} \mathbb{E}(\text{Hop}|S_i, \text{op}) \mathbb{P}(S_i, \text{op})$; (ii) $\mathbb{E}(\text{Glo}) = \sum_{i=0}^{K} \sum_{\text{op} \in \{\text{pop, push}\}} \mathbb{E}(\text{Glo}|S_i, \text{op}) \mathbb{P}(S_i, \text{op})$; where $\mathbb{P}(S_i, \text{op})$ denotes the probability of an operation to occur in state $S_i$. We analyze the algorithm for the setting where $\text{shift} = \text{depth}$ and $p = 1/2$. We do this because the bound, that we manage to find in this case, is tighter, and gives a better idea of the influence of the parameters to the expected performance. For this case the stationary distribution is given by Lemma 5.

**Theorem 6** For a 2D-Stack that is initialized with parameters depth, width, shift = depth and $p = 1/2$, $\mathbb{E}(\text{Extra}) = O(\ln \text{width}/\text{depth})$.

**Proof:** Firstly, we consider the expected number of extra steps for a Push operation. Given that there are $N^\text{active}$ items, a Push attempt would generate an extra step if it attempts to push to a sub-stack that has $N^\text{active} = \text{depth}$ items. Recall that the thread sticks to a sub-stack until it is not possible to conduct an operation on it. This implies that the extra steps can be taken only in the states $S_i$ such that $i(\text{mod depth}) = 0$, because the thread does not leave a sub-stack before $N^\text{active}_i = 0$ or $N^\text{active}_i = \text{depth}$. In addition, a Push (Pop) can only experience an extra step if the previous operation was also a Push (Pop).

Given that we are in $S_i$ such that $i(\text{mod depth}) = 0$, then the first requirement is to have a Push as the previous operation. If this is true, then the Push operation hops to another sub-stack, which is selected from the remaining set of sub-stacks uniformly at random. At this point, there are $f = \frac{\text{depth}}{\text{shift}} - 1$ full sub-stacks in the remaining set of sub-stacks. If a full sub-stack is selected from this set, this leads to another hop and again a sub-stack is selected uniformly at random from the remaining set of sub-stacks.

Consider a full sub-stack (one of the $f$), this sub-stack would be hopped if it is queried before the sub-stacks that are empty. There are $\text{width} - f - 1$ empty sub-stacks, thus a hop in this sub-stack would occur with probability $1/(\text{width} - f)$. There are $f$ such sub-stacks. With the linearity of expectation, the expected number of hops is given by: $f/(\text{width} - f) + 1 = \text{width}/(\text{width} - f)$. Which leads to $\mathbb{E}(\text{Hop}|S_i, \text{Push}) = p \times \text{width}/(\text{width} - f)$ if $i(\text{mod depth}) = 0$ or $\mathbb{E}(\text{Hop}|S_i, \text{Push}) = 0$ otherwise.

From Lemma 5, $\pi_i < 2/(K + 1)$ we obtain:

$$\mathbb{E}(\text{Hop}|\text{Push}) = \sum_{i=0}^{K} \pi_i \mathbb{E}(\text{Hop}|S_i, \text{Push}) < (\sum_{f=0}^{\text{width}-1} \frac{\text{width}}{\text{width} - f}) \frac{2p}{K + 1} < (\ln(\text{width} - 1) + \gamma) \frac{\text{width}}{K + 1} < (\ln \text{width} + \gamma) \frac{1}{\text{depth}}$$

The bounds for $\mathbb{E}(\text{Hop}|\text{Push})$ would also hold for $\mathbb{E}(\text{Hop}|\text{Pop})$. Given that there are $K - i$ (system is in state $S_i$) empty sub-stacks then there are $e = \lceil \frac{K - i}{\text{depth}} \rceil - 1$ sub-stacks whose window regions are empty, minus the sub-stack that the thread last succeeded on. Using the same arguments that are illustrated above (replace $f$ with $e$ and $p = 1-p$), we obtain the same bound.

Window only shifts at $S_K$ if a Push operation happens and at $S_0$ if a Pop operation happens. Hence: $\mathbb{E}(\text{Glo}) < \frac{2}{\text{width}} p + \frac{1}{\text{width}} (1-p)$. Finally, using $\mathbb{E}(\text{Extra}) = \mathbb{E}(\text{Hop}) + \mathbb{E}(\text{Glo})$ we obtain the theorem. 

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6 Parameter Selection

One of the goals of the 2D-stack is to be tunable in order to regulate the trade-off between accuracy and performance. In this section, we investigate the impact of the 2D-stack parameters to accuracy and performance, to come up with the optimal parameter settings.

Empirically, we observed that the contention is inversely proportional to width see Figure 1. As a simple model, we split the latency of an operation into the contention and contention-free operation costs, denoted by \( op = op_{\text{cont}}/width + op_{\text{free}} \). Based on this rough estimation, the performance would increase as the contention factor vanishes with the increase of width, but with an asymptote at \( 1/op_{\text{free}} \). This implies that after some point one can not really gain throughput by increasing the width although it keeps losing in terms of the accuracy. The situation is a bit more complex because of the extra steps that the algorithm might take as width increases (See Theorem 6). In this case, we update the latency of an operation with an additional factor of \( (\ln width/depth) \). Meaning that, after some point, the gains from the contention factor (\( \lim_{\text{width} \to \infty \frac{op_{\text{cont}}}{\text{width}} \to 0 \)) might be surpassed by the extra steps and one would observe a decrease in throughput with the increase of width. This is counter-intuitive in terms of the trade-off between the accuracy and performance. To keep the trade-off alive, we turn our attention to the depth parameter (depth relaxation). This parameter can be used to exploit data locality, which might have a very significant impact on the throughput, especially in a NUMA setting. Operations done by the same thread in isolation at the same sub-stack can yield very high throughput.

In Figure 1, the red curve (L1) depicts the case where we only use the width relaxation for all \( K \) (depth = 1). The other curves diverge from that one at some point where we start depth relaxation. With respect to the performance, we see that it is reasonable to apply width relaxation in the beginning until width = 4P (P stands for the number of threads), where we obtain enough disjoint access parallelism. After this parameter saturates, one can continue to relax in the depth dimension to increase the performance via better locality and fewer extra steps. In terms of accuracy, we observe that the expected error-distance increases almost linearly with the width parameter, whereas it increases almost logarithmically with the increase of the depth parameter (4P for \( k > 200 \)). One can almost recklessly relax on the depth dimension to exploit the locality.

Now, we target to minimize the window maintenance cost. In a sequential process, this cost is not significant. But, in a concurrent execution, this could be very costly as each update impose a cost to all threads. For the small values of the relaxation, the window gets updated more frequently. For this we optimize the process by tuning the shift parameter. Without having a general solution, we illustrate the optimal value of the shift parameter where \( p = 1/2 \) (\( p \) denotes the probability of a Push), for the sequential process that we consider. We will show that shift = depth/2 (assuming depth is even) is optimal for \( E(G_{\text{lo}}) \). Intuitively, these two metrics (Hop and Glo) seems to be correlated because the window shifts only after the maximum number of hops. And, it is more probable to observe a window shift in an interval with operations that complete after many extra steps. We believe, the minimization of \( E(G_{\text{lo}}) \) would also reduce \( E(H_{\text{op}}) \), for all values of \( p \).

**Lemma 7** For the Markov chain that is initialized with \( p = 1/2 \) and shift, where \( l = \text{shift} \times \text{width} \) the stationary distribution is given by the vector \( \pi^l = (\pi_0, \pi_1, \ldots, \pi_K) \): (i) \( \pi_i^l = \frac{1}{(l+1)(K+1-l) \cdot \pi_{i-l}^1} \), if \( i < l \); (ii) \( \pi_i^l = \frac{i+1}{(l+1)(K+1-l)} \), if \( l \leq i \leq K-l \); (iii) \( \pi_i^l = \frac{K+1}{(l+1)(K+1-l)} \), if \( i > K-l \).

**Proof:** In Section 5, we have stated that the stationary distribution exist since the chain is aperiodic and irreducible for all \( p \) and shift. Let \( (M_{i,j})_{(i,j) \in [0,K]^2} \) denotes the transition matrix for \( p = 1/2 \) and shift = depth/2, that is given in Section 5. The stationary distribution vector \( \pi^l \) fullfills, \( \pi^l M = \pi^l \), that provides the following system of linear equations: (i) \( 2\pi_0^l = \pi_1^l \); (ii) \( 2\pi_K^l = \pi_{K-1}^l \); (iii) \( 2\pi_i^l = \pi_{i-1}^l + \pi_{i+1}^l \); (iv) \( 2\pi_i^l = \pi_{i-1}^l + \pi_{i+1}^l + \pi_1^l \); (v) \( 2\pi_{K-l}^l = \pi_{l-1}^l + \pi_{l+1}^l + \pi_K^l \). In case, \( l = K-l \), then (iv) and (v) are replaced with \( 2\pi_{l-K-l}^l = \pi_{l-1}^l + \pi_{l+1}^l + \pi_1^l + \pi_K^l \).

Based on a symmetry argument, one can observe that, for all \( l \), \( \pi_l = \pi_{K-l} \) the system can be solved in linear time \( (O(K)) \) by assigning any positive (for irreducible chain \( \pi_i^l > 0 \)) value to \( \pi_0^l \).
Figure 1: 2D-stack throughput and observed quality for different depth and width configurations

The stationary distribution is unique thus for any \( \pi_{l0} \), \( \pi_l \) spans the solution space. We know that \( \sum_{i=0}^{K} \pi_i = 1 \), starting from \( \pi_0 = 1 \), we obtain and normalize each item by the sum.

**Theorem 8** Given \( p = 1/2 \), \( \text{shift} = \text{depth}/2 \) minimizes \( E(Glo) \), where \( K = \text{width} \times \text{depth} \) and \( l = \text{width} \times \text{shift} \).

**Proof:** The global barrier is updated either with the transition \( S_0 \rightarrow S_{\text{shift} \times \text{width}} \) generated by a Pop operation or \( S_K \rightarrow S_{(K-\text{shift} \times \text{width})} \) generated by a Push operation. Therefore, our objective is to minimize: \( E(Glo) = p\pi_K + (1-p)\pi_0 \). With \( p = 1/2 \) and the symmetry of the Markov chain states \( \pi_i = \pi_{K-i} \), the objective reduces to minimizing \( \pi_0 \). Based on Lemma 7, we have that \( \pi_0 = \frac{1}{(l+1)(K+1-l)} = \frac{1}{K^2+K+1} \). The quadratic function \( f(l) = -l^2 + Kl + K + 1 \) has its maximum value at \( l = K/2 \) since \( f'(l) = K - 2l = 0 \). Having \( l = K/2 = \text{shift} \times \text{width} \), we obtain the optimal value: \( \text{shift} = K/(2\text{width}) = \text{depth}/2 \).

### 7 Experimental Evaluation

We evaluate the performance of our implementations together with other existing stack designs including; the \( k \)-segment relaxed stack [13], Elimination-Stack (elimination) [12] and Treiber-Stack (treiber) [8]. All experiments run on an Intel Xeon CPU E5-2687W v2 machine with two 8-core 3.40GHz Intel Xeon processors (16 cores, 2 threads per core). We pin one thread per core, filling one socket at a time up to 16 threads before we switch to hyper-threading. Two NUMA settings are tested; intra-socket (1 to 8 threads) and inter-socket (9 to 16 threads). Threads select operations uniformly at random (i.e. with probability 1/2) from Pop and Push operations. Memory is managed using SSMEM [9]. To simulate high contention, we put no computational load between operations. For each experiment, the stack is initialized with \( 2^{15} \) items, run for five seconds obtaining an average of five repeats. Throughput is measured in terms of operations per second, whereas accuracy is measured in terms of error distance from the LIFO semantics.

To measure the accuracy, we adopt and modify a similar method in [4, 15]. A sequential linked list is run alongside the stack, for each Push or Pop a simultaneous insert or delete is performed on the list respectively. Items on the stack are duplicated on the list and can be identified by their unique labels. Insert operations happen at the head of the list similar to the push whereas the delete operation searches for the given item deletes it and returns its distance from the head (error distance). We then calculate the expected error distance for a given experiment run for 5 seconds with 5 repeats. Scalability is tested on relaxation, by changing (weakening continuously)
relaxation and on concurrency, by changing (increasing) the number of threads for different NUMA settings. Experiment results are then plotted using logarithmic scales, throughput (solid lines) and error distance (dotted lines) sharing the x-axis.

Based on the analysis presented in Section 6, that was also confronted by our experimental observations, we select $4P$ ($P$ stands for number of threads and $width = 4P$) as the transition point, from width to depth relaxation and $shift = depth/2$ as the optimal performance configuration for 2D-stack. In Figure 3, we evaluate the performance of all algorithms, that are linearizable with respect to $k$-Out-of-Order stack ($k$-robin, 2D-stack and $k$-segment), at the different relaxation levels. Randomized algorithms ($Random$ and $Random-c2$) do not exhibit $k$-Out-of-Order bounds, for that, they are evaluated with respect to number of sub-stacks in Figure 2. We observe that 2D-stack consistently outperforms the other algorithms followed by $k$-robin for both settings where the number of threads changes from 8 to 16 (NUMA setting). Under low degree of relaxation, 2D-stack avoids contention by hopping to another sub-stack on a failed $CAE$. This highly improves performance compared to $k$-robin that keeps retrying on the same sub-stack. As the relaxation increases, 2D-stack combines contention avoidance with locality exploitation, a parameter exclusive to the 2D-stack design as explained in Section 6. While for the other algorithms the accuracy reduces almost linearly with the increase in relaxation, 2D-stack maintains good accuracy with $width > 4P$ ($k > 200$ for $P = 8$ and $k > 600$ for $P = 16$). At this point, the algorithm switches from width to depth by
increasing the depth. This change has a smaller negative impact on the accuracy, compared to the other algorithms. 2D-stack continuously trades off accuracy for throughput by switching between relaxation dimensions for different relaxation levels. k-segment is mostly affected by the high cost of maintaining segments coupled with increased number of hops as relaxation increases.

We now configure the algorithms to obtain the maximum throughput performance for both intra and inter-socket settings, Figure 4. Based on the results that we observed and discussed before (Figure 2), width for Random and Random-c2 translates to $10^3$ sub-stacks. For k-robin, 2D-stack and k-segment this translates to a $k = 10^4$, Figure 3. Two “non-relaxed” algorithms elimination and treiber are also included in the experiment to compare the power of relaxation to improve performance compared to other strict semantics efficiency improvement techniques. We generally observe that, 2D-stack is able to maintain the increase in throughput also while increasing the number of threads, even for the NUMA settings. Under inter-socket setting, Random maintains almost a constant throughput as we increase concurrency with no throughput increase whereas the throughput performance for other algorithms drop. As the number of threads increase, Random, Random-c2 and k-segment maintain almost constant accuracy due to the fixed number of sub-stacks. k-robin and 2D-stack vary the number of sub-stacks as the number of threads change. k-robin reduces number of sub-stacks with the increase in number of threads to keep the $k$-bound, this improves accuracy but hurts throughput due to the increased contention. As observed, 2D-stack maintains high throughput also when the number of threads increases for different NUMA settings. Overall, 2D-stack shows a full control to leverage the semantics relaxation to reach very high throughput in a continuous way. A property that is missing in other solutions.

8 Conclusion

The aim of this work is to design an efficient lock-free stack algorithmic that can continuously relax semantics to improve throughput through exploiting disjoint access parallelism and locality.
We have achieved this through our two dimension relaxation stack design that exploits disjoint access parallelism in one dimension and locality in the other. The 2D-stack, uses an efficient widow based synchronization technique, that manages to keep the relaxation bound without receding the significant performance achieved through locality. 2D-stack significantly outperformed all the other stack implementations due to its capability to switch relaxation dimensions leading to a monotonic trade of accuracy for better performance. In addition to 2D-stack, we have implemented and tested a set of other possible relaxed stack designs. Together with step complexity analysis, we also provided tight accuracy bounds for two algorithms presented in this report including 2D-stack.

References


