**Kvik: A task based middleware with composable scheduling policies**

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**Abstract**

In this paper we present Kvik: an implementation of a task-based "middleware" for shared memory parallel programming in the Rust language built on top of the Rayon library. We devise a system allowing several task-splitting schedulers to be finely tuned by the end users. Among these, we propose an implementation of an adaptive scheduler reducing tasks creations ( splits) to bare minimum by linking tasks splitting to steal requests. Another important scheduler that allows turning computations into sequences of parallel operations is described. This operator proves itself particularly useful for interruptible computations. We exhibit different code examples well suited for different types of schedulers. We conclude our work with a set of benchmarks making heavy use of composability. In particular we present a parallel stable sort implementation with up to 1.5x more speedup when compared to the state-of-the-art parallel sorting implementation.

**Keywords**  work stealing, scheduling, rust, rayon, adaptive, functional programming

1 Introduction

Parallel programming has long been one of the most difficult form of programming. Accelerating computations on a parallel architecture demands a complete understanding of an entire stack of abstractions - from parallel algorithm design and analysis, down to the processor and memory configuration.

To lessen this problem task-based parallel programming builds an accessible bridge between parallel algorithm design and its implementation. A taxonomy of task-based parallel programming tools is presented in [22]. The user is discharged of scheduling issues deferred to the run-time of task management middleware. For example, SPMD parallelism can be trivially scheduled with no dependencies. Unfortunately, this design trivializes the question of task splitting. Consider a recursive divide and conquer algorithm that uses the fork-join model for the tasks. Each call can be potentially run in parallel, and hence is mapped to a task. There is a stop condition for this recursion, and that is where the task-splitting stops. As a result, the algorithm implementation and task splitting are very tightly coupled. Any attempts to tweak performance using different task splitting strategies requires the programmer to dig into the implementation of the algorithm itself.

The Rust language is getting a lot of attention these days due to its unique features related to safety [4], that also make it a good candidate for parallel programming. The language benefits from a very strong memory model that has ownership and borrowing as its first class concepts. The compiler disallows multiple "overlapping" mutable aliases on the same object. This functionality is called the "borrow checker" and is notorious for its steep learning curve. This one change however, makes parallel programming inherently safe in Rust. Rust also has a powerful set of generics ("traits") for concurrency that govern which types can be shared (Sync) or moved (Send) between threads. For example, Rust provides two different types for reference counting: Rc and Rc, the latter one using atomic counters. The type system will detect at compile time the sharing of Rc type between two different threads, since Rc does not implement Sync.

Finally Rust provides a functional-style API that is well suited for expressing clean parallel code. In particular the Rayon [2] library already allows many users (more than 7,000,000 downloads as of July 2020) to write safe and elegant parallel code in a functional manner, using task splitting and stealing to parallelize the computation. Given its functional nature, the notion of tasks and dependencies is exposed organically. The contributions of this paper are:

1. We introduce Kvik, a prototype implementation of configurable schedulers that exposes a functional API for algorithm design and can finely tune task splitting.
2. We propose a modular mechanism for tweaking the behavior of schedulers. This Adaptor API is accessible to the end users and allows them to modify the internal scheduling policies. It also allows for easy composition of multiple policies.
3. We propose a new API for abstracting divide and conquer computations. This API allows to delegate decisions regarding the splitting of tasks to the middleware.
4. We demonstrate up to 1.5x more speedup on a parallel stable sort (over the state of the art) tuned using a variety of task splitting schedules, and packaged with Kvik. Additional benchmarks demonstrate the performances of different adaptors and schedulers.
We provide some Rust code in different places through this paper. The code is always very short and should be clear even for readers who don’t know the language. We also use links to source codes for further details.

The paper starts off in Section 2 by introducing several features of current task-based middlewares upon which we rely. We continue by presenting the inner workings of our library along with some code examples in Section 3. In particular we develop several schedules and many adaptors that control task division. These developments give the programmer a fine-grained control over the behavior of their parallel algorithm in very few lines of code. Section 4 presents some experimental results on a set of different algorithms. We show examples relying on different scheduling strategies for their optimal executions. Finally we conclude on our work in Section 5.

2 Related Work

In recent years we have seen many new developments of task-based middlewares: Cilk [7], TBB [16], OpenMP [11], Xkaapi [13], TPL [17] for the .NET framework, and Rayon [2] for Rust. Task based parallel programming has also been applied to distributed memory models [23]. A very recent work Cpp-Taskflow [14], parallelizes code through task-graphs given by the programmer. Similarly, SMPSs [18] uses directives to allow the programmer to describe tasks. The runtime then dynamically makes a dependency graph. Legion [6] and Chapel [9] introduced support for data partitioning and task based programming at a language level. HPX [15] is a runtime-environment that combines task-based programming with a Global Address Space.

We should note that of all the libraries listed in this section, only Rayon provides a programming interface in a functional programming style. To the best of our knowledge, exposing task splitting schedules to the programmer and allowing composability of such schedules is a novel contribution of Kvik compared to the previous state of the art. Dependencies can be expressed organically using a functional programming style. Finally, the memory safety guarantees afforded by Rust make Heisenbugs extremely uncommon, at no cost to performance.

Load balancing in task based programming is usually achieved through a work stealing engine. Available tasks are distributed among threads and any thread becoming idle will seek additional work from others. Traditionally this choice is random but different other policies have been developed [20]. Work stealing is well known [8] for its theoretical guarantees, bounding the number of steal requests by \( O(p \times D) \) where \( p \) is the number of threads and \( D \) the depth of the algorithm. The cost of maintaining the lists of tasks to be stolen from is studied in [21].

We now zoom-in on some middlewares for the comprehension of our work.

2.1 TBB

Intel TBB is an important task-based middleware with many applications. The overheads of synchronization and stealing in TBB have been well studied in [10]. In this section we are going to zoom on its grain size determination mechanism [19] which is also used in Rayon. This mechanism is important because it allows to dynamically tie the tasks creations to work-stealing. The benefits are two-fold:

- Better performance due to less task creations, divisions and reductions;
- No need for the end user to specify a sequential fallback size.

The task splitting policy works as follows:

1. Start with an initial task and associate it to a counter (usually a multiple of the number \( p \) of threads)
2. When the task gets divided, divide counter by 2.
3. If it reaches 1, stop creating new tasks and compute what is left to do in sequential.
4. When a task gets stolen however, reset the counter to a higher value in order to enable the creation of new tasks.

This policy is quite well designed. If the work is balanced, threads synchronized and their number a power of two, we end up creating \( O(p) \) tasks. In other cases the number of tasks created might be higher. For example imagine three threads. Since the initial task gets divided in two, we create four tasks to feed all threads. Three tasks get completed in parallel and we are left with a single task for three threads. The whole process then repeats itself until tasks cannot be divided anymore. For an input size of \( n \) this gets repeated \( O(\log(n)) \) times if all divisions are always possible (which corresponds here to the depth). This is still much better than a naive \( \Omega(n) \) tasks creations. We have been able to confirm this expected behavior with our middleware through various experiments.

In Kvik, we provide this task splitting policy to the programmer. It is called as the thief_splitting strategy.

2.2 Xkaapi

Kaaapi [13] (now renamed as Xkaapi) is an experimental task-based middleware. Efforts were focused on minimizing overheads, in particular overheads related to task creation.

Of particular interest to us is the ability for Xkaapi to execute adaptive parallel algorithms [12]. The main idea is to delay task division as much as possible to limit task creation overhead. This is achieved by linking task division to steal requests. If there is no steal request because all threads are busy, no task division occurs and all computations take place in a single task.

While this idea is compelling its implementation is rather difficult: it requires a way to interrupt a running task when a steal requests occurs. Xkaapi achieves this through nested loops:
work we detail some of its inner mechanisms.

2.3.1 Parallel iterators

Rayon is a recent work-stealing middleware developed in the Rust programming language. It benefits from two key aspects of Rust: enhanced security through rust’s security mechanisms (borrow checker and type system) and a functional programming style. Since it serves as the base for our work we detail some of its inner mechanisms.

The base operation in Rayon is the `join()` function which:

- Takes as arguments two closures to be run in parallel.
- Creates a task for the second closure and executes the first one immediately.
- Blocks the thread (goes stealing) until both closures are executed.

In Kvik, we directly use this function for executing the tasks created. It hence allows us to reuse the work stealing engine of Rayon as-is. The task splitting schedule in Rayon is the same as TBB. The main feature of Rayon is that it provides `parallel iterators`. We now describe how `parallel iterators` are implemented.

2.3.2 Producers

A `ParallelIterator` trait in Rayon extends the concept of sequential iterators to parallel iterations. We can for example compute \(\sum_{i=0}^{9} f(i)\) with:

\[
(0..10).into_par_iter().map(f).sum()
\]

As a usage example for Rayon, let’s take as input a vector `v` of integers and compute a new vector containing all even elements of the input in parallel. This operation is known to be not trivial to program. The fact the elements are filtered out makes it difficult to move elements to their final positions in parallel.

\[
v.into_par_iter() // par iter on integers
.filter(|&e| e % 2 == 0) // only even integers
.fold(Vec::new, |mut v, e| {
  v.push(e); // each task produces one vector
})
.map(|v| once(v).collect::<LinkedList<_>>())
// List containing 1 vector
.reduce(LinkedList::new, |mut l1, mut l2| {
  l1.append(&mut l2);
  // concatenate lists of vectors in parallel
})
.into_iter() // loop on all vectors sequentially
.flatten()
.collect::<Vec<_>>() // into one vector of ints
\]

The computation starts with the filtered iterator on the input. This iterator is going to be divided into smaller chunks dynamically by Rayon’s scheduler. Each division will result in a call to the `join()` to create new tasks. Once the division stops, a sequential `fold()` operation is applied on the chunk. This produces a small vector that contains all the elements of the chunk. As a result, there exists one vector (with only even elements) corresponding to each task that did not divide further. Every vector is then mapped into a linked list. A parallel reduction then concatenates the multiple lists into one single list. To complete the algorithm, the list of vectors is turned back into a sequential iterator and flattened into a single vector. Note that the programmer cannot specify how small each task should be in this example. Hence, while it is quite easy to perform complex computations, task splitting is invisible to the programmer.

2.3.3 Consumers

Implementing the entire `ParallelIterator`-based pipeline is done through divide and conquer as follows:

1. We start from the initial data and divide it into two parts recursively, forming a division tree.
2. When leaves are reached data is folded sequentially.
3. The results are reduced two-by-two forming a reduction tree symmetrical to the division tree.

However `ParallelIterators`, like all iterators, are lazy and are only holding data and functions while waiting for computations to start. The operation which will launch all computations is the `reduce()` function. It takes a function generating identity elements, and a function that turns two elements into one.
Most types that implement `ParallelIterator` cannot be divided into two. Like the `Map` for example, which is obtained by applying a function on each element of an underlying base iterator. A `Map` structure contains two fields: the base iterator and the function to apply. Due to Rust’s very specific memory model that requires data to have exactly one owner, the function (can be a closure) cannot be owned by two different structures. The simple solution to this problem is to take it by reference. This requires a different structure which still has two fields but one field is now a reference of the real function. We can abstract over these types by introducing a new trait: the `Producer` trait.

A type that implements `Producer` can not only be divided into two pieces, it can also be iterated over as it produces some items. This is why it is called a `Producer`. While types that implement `ParallelIterator` simply hold data and/or computations, types that implement `Producer` really carry them out. Hence, the `ParallelIterator` is turned into a `Producer`, and the above divide and conquer algorithm is run on the `Producer`.

### 3 Kvik

In this section we present `Kvik`, our prototype for an alternative implementation of `Rayon’s ParallelIterator`. `Kvik` stands for `Kaarya VibhaajaK`, which is Hindi phonetic for "Task Splitter". We try to fulfill several goals:

- be faster
- allow more expressivity
- allow the end user to define and control task splitting policies

`Kvik` allows the end user to express very complex parallel algorithms in few lines of code with excellent performances and interchangeable schedulers.

We start by introducing in Section 3.1 the `Divisible` trait which is the most fundamental abstraction we use. We then present Section 3.2 a basic scheduler for tasks creations. Section 3.3 we show how to modify on demand the scheduler behavior through `adaptors`. We show how to abstract other more generic divide and conquer schemes in Section 3.4. We then provide two different performance enhancing schedulers. Section 3.5 we provide a scheduler using a sequence of parallel blocks and Section 3.6 an adaptive scheduler linking tasks creations decisions to steal requests. Finally we conclude Section 3.7 with an elegant parallel merge sort algorithm putting all introduced features into use.

#### 3.1 The `Divisible` trait

We introduce a new trait: `Divisible`, which requires the following functions to be implemented:

- `fn should_be_divided(&self) -> bool;`
- `fn divide(self) -> (Self, Self);`
- `fn divide_at(self, index: usize) -> (Self, Self);`

The `divide` method takes one object and divides it into two objects containing the left and right parts of underlying data. Left and right parts are expected to be approximately balanced but this is not always the case. The `divide_at` method takes an additional index at which to cut the object into two. The left part being approximately of size `index`. This is an important method since some algorithms rely on uneven divisions to be efficient (see section 3.5). Finally the `should_be_divided` method takes the object by reference and asks it whether or not it should be further divided. This method allows to delegate task creations decisions to user-space.

Once we have this, we can define `Producers` (in `Kvik`) as types which are both sequential `Iterators` and `Divisible`.

#### 3.2 Join scheduler

We now describe the implementation of the scheduler that can create tasks, facilitate work stealing, and finally reduce the results from the tasks that have terminated. The most naive implementation for such a scheduler is based on the fork-join model. It makes use of the `join()` from the Rayon library and is hence called `join scheduler`.

```rust
fn schedule_join(&self, producer: P, reducer: &R) -> P::Item {
    if producer.should_be_divided() {
        let (left, right) = producer.divide();
        let (left_r, right_r) = rayon::join(
            || schedule_join(left, reducer),
            || schedule_join(right, reducer),
        );
        reducer.reduce(left_r, right_r)
    } else {
        reducer.fold(producer)
    }
}
```

The decision to divide and create tasks is delegated to the producer with `producer.should_be_divided()` (A `Producer` always implements `Divisible`). The tasks are created using the `join()` from Rayon (see Section 2.3). This uses the existing work stealing implementation from Rayon. Finally, the results from the two tasks are reduced into one.

We also provide a superior variant called `schedule_depjoin` which allows the reduction to be executed without wait by the last thread to finish one of the two parallel operations. In contrast, as per the standard `rayon::join`, if the thread executing the left task finishes first, it has to wait for the right result. It hence starts stealing tasks. If it gets a task, it will not initiate the reduction until the stolen task is complete.

#### 3.3 Adaptors to control task splitting

The `should_be_divided` method enables us to write many interesting adaptors controlling the division process in different ways. Adaptors can be nested into each other and provide a high degree of composability.
We also provide the following useful adaptors:

- **even_levels**: enforces all leaves to be on an even depth level. Implemented by flipping a boolean every time it is divided.
- **force_depth**: enforces the division tree to be a complete tree for at least the given depth.
- **size_limit**: stops divisions when the underlying producer is of given size.
- **cap**: counts the active number of tasks and refuses division when the number reaches a threshold. This also decrements the counter as the tasks finish.
- **join_context_policy**: divides tasks up to a given depth. Left tasks are always divided and right tasks only if stolen.

Finally, there is a **thief_splitting** adaptor that allows to re-implement Rayon and TBB’s mechanism for controlling task divisions:

1. start with a counter and the thread ID of the thread that created the task
2. when divided the counter gets decreased by one, children get a copy of parent’s thread ID
3. if the counter reaches zero, should_be_divided returns false unless the parent’s thread ID is not the same as child’s thread ID
4. if task is stolen, the counter is reset to its initial value

In the Rayon library this counter has an initial value equal to \( \log p + 1 \) for \( p \) threads in order to force the creation of \( 2p \) tasks. Here, this initial value can be given by the programmer.

Adaptors strongly control the scheduler and can be turned on or off by the end user. This allows an easy way to compare different scheduling policies and to tune algorithms to the best one.

### 3.4 Parallelizing divide and conquer

The **Divisible** trait also contains a pre-implemented function **wrap_iter()** that allows the programmer to easily write parallel divide and conquer algorithms.

Let’s take a classical divide and conquer maximum sub-array sum problem. The input is recursively divided in two, looking for maximum sums in the left and right pieces. On return we then search for the maximum sum touching the midpoint before returning the max of the left, right and middle sums.

This can be parallelized naively, by turning recursive calls into parallel recursive calls just using `rayon::join()`. However, the sequential fallback size would then have to be manually written inside an `if` condition.

A more generic option is to use `wrap_iter()` as follows:

```rust
def max_sum_par(slice: &[i32]) -> i32 {
    slice
        .wrap_iter()
        .map(|s| (s, max_sum_seq(s)))
        .thief_splitting(4)
        .reduce_with(|(left, l_sum), (right, r_sum)| {
            let mid_sum = middle_sum(left, right);
            (funce_slices(left, right),
             l_sum.max(r_sum).max(mid_sum),
            )
        })
}
```

In this example, `wrap_iter()` will turn the `slice` into a parallel iterator on sub-slices. These subslices are then mapped to compute the max sum sequentially on each one (as a side note, this can be a faster algorithm). By default, slice would divide until a size 1. Using the `thief_splitting` adaptor, the scheduling policy is changed to restrict tasks creation. Individual results are finally fused back together (in parallel) by computing the middle-part sum and comparing all sums at each reduction step. This example can be extended to a more generic use-case where the input is not a `slice`, but any type that implements the `Divisible` trait. Furthermore, instead of `thief_splitting` any adaptor(s) can be put after the `map`.

### 3.5 Scheduling sequences of parallel operations

There is interesting class of problems which are easy to parallelize, but a naive implementation increases the work and doesn’t scale well. For example, the `find_first` that applies a function \( f \) on all elements of an iterator and returns the first element \( e \) (minimal) for which \( f(e) \) is true. For \( P \) threads running, it is tempting to simply partition the input into size \( N \) into \( P \) pieces and give one to each thread. However, if the minimal \( i \) lies at \( \frac{N}{P} - 1 \), this gives no speedup! To solve this problem, we introduce the `by_blocks` adaptor.

Instead of parallelizing all computations over the `Producer`, the `by_blocks` will divide the producer into blocks of growing sizes, and advance sequentially over the blocks. Each block is scheduled in parallel using all available threads. This scheme is implemented using the `divide_at` method of the `Divisible` trait that cuts the `Producer` at a given point.

We need however, to choose adequate block sizes. A good solution is again to use a geometric series. For example we take the number of threads \( (P) \) for the initial size, process
the first block in parallel and double the size, process the second block in parallel and double again the size and so on. Using this series, the number of blocks is logarithmic in input size. Since useless computations can only take place in the last block, and this block’s size is approximately equal to the sum of sizes of all the blocks processed before, we have a bound on the amount of useless work. It cannot be more than one half of the total work. Changing the increase factor will of course adjust this ratio to whatever the user likes. In contrast, for the naive partitioning, up to $\frac{N}{P} \times P - 1$ can be useless.

Figure 1 displays this schedule in action.

![Figure 1](image.png)

**Figure 1.** Executing `find_first` with 2 threads (one color per thread). `thief_splitting` adaptor inside each block. The sequence of blocks of sizes growing exponentially is visible top to bottom.

### 3.6 Adaptive scheduling

We provide the adaptive schedule from Section 2.2 for use in *Kvik*. In order to achieve this we require a new method in the `Producer` trait: `partial_fold`.

```rust
fn partial_fold<B, F>(&mut self, init: B, fold_op: F, limit: usize) -> B
    where
        B: Send,
        F: Fn(B, Self::Item) -> B;
```

This is similar to a fold operation except that it needs a `limit` on the number of iterations to run. It will also borrow mutably the `Producer`, making it usable after a fold. The `partial_fold` hence replaces the nano-loop of the adaptive scheduling algorithm.

The scheduler code is much more complex (60 lines) than the simple join scheduler since we need to re-implement the whole mechanism of doing sequential work, checking for steal requests and dividing the producer if stolen. However, this complexity is hidden from the programmer, who just need to call the `adaptive` adaptor to switch to adaptive scheduling.

The benefits are:
- less tasks creations (number of successful steals + 1)
- less divisions and reductions
- on division the remaining work is divided in two, so the division is fairer

#### 3.6.1 Adaptive divide and conquer

While the adaptive schedule is nice, it cannot be used in conjunction with `wrap_iter` from Section 3.4 because types which are only `Divisible` and not `Iterators` do not provide any way to fold partially. For such cases the end user needs to provide additional information on the computations executed in the nano-loop. We provide therefore a work method. This method offers stateful nano-loops for `Divisible` states, and needs two arguments, a closure `C` and the initial state. The closure `C` (written by the user) should borrow (mutably) the `State` and take-in an integer `I`. With the closure, the user describes how to work upon a given state for `I` iterations.

This dovetails nicely with the `partial_fold` above, where the closure `C` is called (instead of the `fold_op`) with the `limit` as `I`.

`work()` is particularly useful to implement algorithms which are hard to write in a pure functional programming style. A good example is graph traversals, for which the state can consist of the stack or queue, and a reference to a shared set of visited nodes.

### 3.7 Parallel merge sorts

In this section we present a parallel merge sort algorithm which takes advantage of most of *Kvik*’s features. It is a good example expliciting why composition matters.

We start with a tuple of two mutable slices: the input slice (formed over the input Vector) and a temporary buffer of the same size. Since mutable slices are `Divisible`, a tuple of mutable slices is also `Divisible` (the division splits each slice into two, and yields two tuples with the left and the right splits of both slices). We then call `wrap_iter` (see 3.4) on the tuple to get a `ParallelIterator`. Note that the item yielded by this `ParallelIterator` is a tuple of sub-slices.

With this, we can write the first half of the parallel sort as follows.

```rust
(input, buffer).wrap_iter().even_levels().map(|(inp, out)| {
    inp.sort();
    (inp, out)
})
```

This code just breaks the input and the buffer into small pieces and sorts the input in-place (using the stable sequential sort from the Rust standard library) once it can not be split any more. Note that the `even_levels` adaptor will ensure data being merged back into the correct slice.

At this point different adaptors from Section 3.3 can be applied to control the tasks divisions. We can use `bound_depth` to mimic a classical divide and conquer, `thief_splitting` or
Kvik: A task based middleware with composable scheduling policies

join_context to have a more dynamic splitting. On top of that we can turn depjoin (Section 3.2) on or off. This gives us 6 different algorithms to try.

After choosing our adaptors, we continue with the reductions which require merging sorted slices together.

We provide a generic merge adaptor fusing two sorted parallel iterators into one. With this, we can easily implement the classical parallel merge of two sorted lists.

```rust
reduce_with(|(l_in, l_out), (r_in, r_out)| {
    let output = fuse_slices(l_out, r_out);
    l_in.as_ref().into_par_iter()
        .merge(r_in.as_ref())
        .zip(output)
        .for_each(|(inp, out)| {
            *out = *inp;
        });
    (output, fuse_slices(l_in, r_in))
});
```

l_in.as_ref() turns the left mutable slice as a slice and into_par_iter turns it into a parallel iterator on the left elements. The merge adaptor uses by-default, an adaptive task splitting schedule (Section 2.2) since divisions come with a price (each division requires a binary search). It is however possible to turn it back to a more classical scheduling policy like thief_splitting. After the merge, we just zip this iterator with a parallel iterator on the elements of the output slice, and write the data into the buffer.

Merging slices instead of iterators We also provide a hand-tuned manual implementation for an adaptive merge using the work function directly on slices (references of the vectors). The state is composed of the remaining input and output slices. Working locally for n iterations moves the n smallest elements from the two input slices into the output slice. This allows us to eliminate some bound checks that the iterators use internally.

The parallel sorts contain two levels of parallelism: parallelizing the sorts and each reduction. Each stage can be tuned in many ways due to high number of adaptors we provide. If we count here, we have 6 algorithms for the sorts and 3 different reductions which means a total of 18 different parallel merge sorts. Before Kvik we ended up with the same algorithm re-implemented different times for all the schedules that we wanted to try.

Figure 2 is the log obtained when running on two threads with a depth limit of 2 and the adaptive scheduling algorithm for the merge.

4 Experiments

We now proceed with a set of experiments comparing Kvik to state of the art libraries and different scheduling policies between themselves. The goal of this section is double: showing that choosing scheduling policies matters and showing that Kvik is competitive with state of the art libraries. We start Section 4.1 by testing the by_blocks scheduler on very fine grain computations. In Section 4.2 we first compare different adaptors before testing our stable sort algorithm against TBB and OpenMP. Finally we conclude our experiments series in Section 4.3 with an adaptive scheduling for a benchmarks game [1] problem.

All the experiments for this work were conducted using 4 CPUs of Intel Xeon Gold 6130 (Skylake, 2.10GHz, 16 cores/CPU) with 768GiB total RAM, running Debian 10.5. C++ programs were compiled using GCC version 8.3.0, C++17 standard and the O2, -fopenmp and -march=native flags. TBB 2020.3 was used for the sort benchmark, with ParallelSTL header. Rust programs were compiled with the rustc compiler v1.45.0, link time optimization enabled, and the target-cpu=native flag. In each experiment threads are always bound to cores in order to minimize the number of numa nodes in use. The lineplots for each experiment result include a confidence interval with 95% confidence level.

4.1 Interruptible algorithms

We start by a first set of experiments testing the by_blocks adaptor from Section 3.5. We try the blocking mechanism respectively on find_first and all. In both cases we consider an input vector of 100 million elements. In both cases, sequential algorithms are blazing fast with sequential running times in the order of tens of milliseconds. This shows that blocking mechanisms can be used even in fine grain computations.

We compare the activation or de-activation of blocks and two different schedulers: thief_splitting and adaptive. The thief_splitting task splitting works as described Section 2.1 and Section 3.3. The adaptive scheduler works as detailed in Section 3.6 with an added benefit in this particular case. Since the adaptive scheduler is regularly interrupting computations to check for steal requests we can take advantage of this interruption to check if the task gets canceled due to the aborting mechanisms of our algorithms. This allows us...
to stop any task as soon as it is recognized useless while the classical scheduler can only cancel non started tasks.

In both sets of experiments we also compared ourselves with implementations using the Rayon library but for some reasons the find_first implementation always ends in a speed-down, hence it is not shown in the curves.

4.1.1 Find first
We start with find_first. Figure 3 and Figure 4 show executions of our four versions of the find first algorithm on two different examples. In each case we only have one target but its position differs. In Figure 3 the position of the target is chosen uniformly at random while Figure 4 shows a target at $n/2 - 1$. We can see that it is always better to activate blocks. Implementations without blocks are much slower because, for any number of threads, at least half the work done is wasted.

Figure 3. Find-First speedups, uniformly distributed target. Note the high variability in the implementations without blocks.

4.1.2 All
Now for all the measures are a bit more complex. Figure 5 shows the median speedups obtained. A flexible implementation can be made with thief_splitting uses for task splitting. Finally, the Adaptive scheduler (2.2) can be used for minimal splits. However, in this case there is no cost of division, so this policy does not yield a benefit. Each of these policies can be composed with the by_blocks adaptor (Section 3.5) in order to add a sequential loop. Implementations with blocks and without blocks have a similar performance but the confidence interval is much wider for the variants without the blocks. The variation in performance comes from the fact that the target may be found at the start of a task in the best case, or at the end in the worst case. Coupled with this, the other threads may have just started their tasks as well.

They will all finish their tasks before they can be stopped. Since the blocks reduce the granularity of task splitting, such different scenarios don’t produce as much of a variation in time anymore.

Figure 4. Find-First speedups, target at $n/2 - 1$. The implementations without blocks slows down at 2 threads since the first thread has to work until the end to reach the point of interruption. This is the point of maximum wasted work.

Figure 5. Median speedups for the "All" with uniformly distributed target. Note the higher variability in speedups for implementations without blocks as opposed to the ones with blocks. The implementation from the Rayon library is significantly slower.

4.2 Parallel stable sort
All sorts benchmarks are done sorting a vector containing random permutations of of $10^8$ 32bits integers. Speedups are obtained by comparing to the fastest sequential algorithm
which is in this case `rust`’s stable sort with a running time of 6.5 seconds.

### 4.2.1 Tuning the sort using adaptors

We start by tuning the sort algorithm from Section 3.7 using the task splitting adaptors. We compare three adaptors: `bound_depth`, `join_context` and `thief_splitting`. The `thief_splitting` policy doesn’t need much calibration but for the two others parameters are calibrated manually to their best values. The input to be sorted is first broken down into small pieces that are sorted in parallel, then the sorted pieces are merged together, also in parallel. Hence, each curve in Figure 6 has been obtained with a combination of two adaptors from the list, one used for the sorting phase and the other for the merge.

![Figure 6. A comparison of the same Iterator Sort with different adaptors for task splitting at the two levels. The name of each algorithm is given by the two adaptors it uses. Task splitting adaptors change the scalability of the same implementation.](image)

We can see in this case that hand tuned policies win with a slight advantage for the `join_context` adaptor.

The same process has been repeated for the `depjoin` adaptor and the different merging strategies but is not shown here due to space constraints. The best combination is the `join_context` composed with `depjoin` and the adaptive schedule for the merge.

### 4.2.2 Comparing sorts

We now compare our sorts with standard parallel stable sorts algorithms from different libraries.

Figure 7 shows the speedups obtained for different threads number `rust rayon` is the parallel stable sort from the Rayon library. `cpp pstl` is the stable sort from the Intel ParallelSTL of C++ 17 with the `par` execution policy. It internally links to TBB. `cpp gnupar` is the GNU parallel stable sort using OpenMP. Finally we have the fastest stable sort, the slice sort as `rust slice` and the Iterator sort as `rust iter`.

We can see a very good scaling for our algorithms with speedups reaching up to 26, far more than speedups from state of the art middlewares. On top of that we can see that the more generic iterator based merge algorithm does not degrade performances strongly when compared to the manual slice based implementation.

One needs to be careful about what conclusions to draw from this since we are based on the fastest sequential algorithm. But at the very least it shows we are competitive with state of the art libraries even on very fine grain computations and all of this with a sorting algorithm which is very clear and fits ten lines of code.

### 4.3 Fannkuch redux

This micro benchmark has been described in [3]. The problem is quite simple:

For all permutations of the sequence $(1..N)$, what is the maximum number of prefix-flips to be made in order to have 1 at the start of the sequence. A prefix-flip on a sequence $(j..N)$ is defined as reversal of the first $j$ elements of this sequence. The program implementation has been taken from The Computer Language Benchmarks Game [1].

The implementation must (as per the rules of the benchmark) compute each permutation and then the flips required for it to reach the state $(1..)$. Hence, the complexity of this program is exponential in the input size. It is hence not memory-bound, since the sequence we work with is small ($\text{length} < 16$).

Parallelism is exploited by dividing the set of all permutations of the sequence among the threads. In the case of task-based implementations (for Rust), each task contains a set of permutations to work with. This brings up an interesting caveat. Given a set of permutation-indices, generating
the first permutation is much more expensive as compared to generating the next permutation in a set from a given permutation of the set. Therefore, task splitting becomes quite expensive, since the first permutation of the set assigned to the new task must be generated from scratch.

We use $N = 13$, and start off with the fastest code on the benchmark website (incidentally in Rust). The implementation contains a parameter $\text{num\_blocks}$, that indicates the number of sub-sets that the set of all permutations can be divided into. The implementation includes a parallel loop over all sub-sets (using the Rayon library). Therefore, when the threads steal, they steal one or more sub-sets of permutations, and work on them. For a competitive baseline, we do a grid search for $\text{num\_blocks}$ as a linear function of number of threads. We find that a multiplier of 8 is optimal for higher number of threads ($> 40$). This baseline is named $\text{rust static}$.

With Kvik, we use the Work (see Section 3.6.1). The state in the work preserves the permutation that a task had processed before being stolen. One of the child-tasks can continue exactly where the parent left off, and quickly generate the next permutation. Subsequently for the task splitting schedule, we can use the $\text{thief\_splitting}$ adaptor or better yet, simply the Adaptive schedule. These implementations are named $\text{rust thief}$ and $\text{rust adaptive}$ respectively.

Figure 8 shows the comparison for these implementations along with the fastest C++ bench taken as-is from the website, that has a simple $\text{omp parallel for}$. The frequent drops in speedup for this curve are also the regions of high variability (as shown by the shaded area). This could be due to the slight load imbalance that manifests organically from the problem itself. Since all rust implementations use task stealing as opposed to work sharing, they exhibit stable performances. Among the rust implementations, adaptive schedule leads due to the minimal task splits. The tuned $\text{static}$ implementation from the website that uses the Rayon library, is quite close to the one with $\text{thief\_splitting}$ implemented in Kvik. This means that we can achieve the same performance without the need for tuning extra parameters.

5 Conclusion

In this paper we presented our work on Kvik, a prototype task-based middleware built on top of Rayon. Kvik allows end-users to finely tune their algorithms’ behavior through a mix of task splitting schedulers and adaptors that control the splits themselves. Out of these, the $\text{by\_blocks}$ adaptor allows to add an external sequential loop which proves itself valuable for interruptible computations. We also provide a nice abstraction for divide and conquer algorithms allowing to delegate tasks creations decisions to the middleware. In our opinion the $\text{composability}$ we put at the disposition of parallel programmers is unmatched, allowing simple and elegant code.

Among the schedulers provided, the adaptive scheduler can be used to reduce tasks creations to a bare minimum, and balance the load organically. It allows iterators to be consumed gradually while keeping sequential executions fast. We demonstrate its superiority through different experiments. Early interruptions in the $\text{find}$ and $\text{all}$ algorithms, adaptive merges in our sort algorithms and adaptive divisions for the pancakes benchmark, all result in a fast and scalable implementation.

Our experiments show that is possible to provide genericity while keeping strong performances as is demonstrated by a fast and scalable iterator sort implementation.

In our future works we hope to work our way towards an integration within the Rayon library. We also take interest in the composability of parallel algorithms. We also expect to work on locality issues. $\text{By\_blocks}$ is already having nice properties for locality but it could be improved in different ways. We also consider enhancing $\text{Divisible}$ to execute different kind of divisions based on stealers ids. Finally we hope to tackle $\text{streams}$ and $\text{futures}$. Interruptible parallel iterators will allow a mix of long computations interrupted to allow fast IO.

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References

[1] n.d. The Computer Language Benchmarks Game. https://benchmarksgame-team.pages.debian.net/benchmarksgame/. Accessed: 2020-08-4.
Kvik: A task based middleware with composable scheduling policies

[2] [n.d.]. Rayon: a data parallelism library for Rust. https://github.com/rayon-rs/rayon. Accessed: 2020-07-27.
[3] Kenneth Anderson and Duane Rettig. [n.d.]. Performing Lisp Analysis of the FANNKUCH Benchmark.
[4] Abhiram Balasubramaniam, Marek S Baranowski, Anton Burtsev, Aurujit Panda, Zvonimir Rakamaric, and Leonid Ryzhky. 2017. System programmning in Rust: Beyond safety. In Proceedings of the 16th Workshop on Hot Topics in Operating Systems. 156–161.
[5] Daniel Balouek, Alexandra Carpen Amarie, Ghislain Charrier, Frédéric Desprez, Emmanuel Jeannot, Emmanuel Jeanvoine, Adrien Lébre, David Margery, Nicolas Niclausse, Lucas Nusbaum, Olivier Richard, Christian Pérez, Flavien Quesnel, Cyril Rohr, and Luc Sarzyniee. 2013. Adding Virtualization Capabilities to the Grid’5000 Testbed. In Cloud Computing and Services Science, Ivan I Ivanov, Marten van Sinderen, Frank Leymann, and Tony Shan (Eds.). Communications in Computer and Information Science, Vol. 367. Springer International Publishing, 3–20. https://doi.org/10.1007/978-3-319-04519-1_1
[6] Michael Bauer, Sean Treichler, Elliott Slaughter, and Alex Aiken. 2012. Legion: Expressing locality and independence with logical regions. In SC’12: Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis. IEEE, 1–11.
[7] Robert D Blumofe, Christopher F Joerg, Bradley C Kuszmaul, Charles E Leiserson, Keith H Randall, and Yali Zhou. 1996. Cilk: An efficient multithreaded runtime system. Journal of parallel and distributed computing 37, 1 (1996), 55–69.
[8] Robert D Blumofe and Charles E Leiserson. 1999. Scheduling multi-threaded computations by work stealing. Journal of the ACM (JACM) 46, 5 (1999), 720–748.
[9] Bradford L Chamberlain, David Callahan, and Hans P Zima. 2007. Parallel programmability and the chapel language. The International Journal of High Performance Computing Applications 21, 3 (2007), 291–312.
[10] Gilberto Conrreras and Margaret Martonosi. 2008. Characterizing and improving the performance of intel threading building blocks. In 2008 IEEE International Symposium on Workload Characterization. IEEE, 57–66.
[11] Leonardo Dagum and Ramesh Menon. 1998. OpenMP: an industry standard API for shared-memory programming. IEEE computational science and engineering 5, 1 (1998), 46–55.
[12] Vincent Danjean, Roland Gillard, Serge Guelton, Jean-Louis Roch, and Thomas Roche. 2007. Adaptive loops with kaapi on multicore and grid: applications in symmetric cryptography. 33–42.
[13] Thierry Gautier, Xavier Besseron, and Laurent Pigeon. 2007. Kaapi: A thread scheduling runtime system for data flow computations on cluster of multi-processors. In In PASCO’07: Proceedings of the 2007 international workshop on Parallel symbolic computation. ACM, 15–23.
[14] T. Huang, C. Lin, G. Guo, and M. Wong. 2019. Cpp-Taskflow: Fast Task-Based Parallel Programming Using Modern C++. In 2019 IEEE International Parallel and Distributed Processing Symposium (IPDPS), 974–983.
[15] Hartmut Kaiser, Thomas Heller, Bryce Adelstein-Lelbach, Adrian Serio, and Dietmar Fey. 2014. Hpx: A task based programming model in a global address space. In Proceedings of the 8th International Conference on Partitioned Global Address Space Programming Models. 1–11.
[16] Alexey Kukanov and Michael J Voss. 2007. The Foundations for Scalable Multi-core Software in Intel Threading Building Blocks. Intel Technology Journal 11, 4 (2007).
[17] Daan Leijen, Wolfram Schulte, and Sebastian Burckhardt. 2009. The Design of a Task Parallel Library. In Proceedings of the 24th ACM SIGPLAN Conference on Object Oriented Programming Systems Languages and Applications (Orlando, Florida, USA) (OOPSLA ’09). Association for Computing Machinery, New York, NY, USA, 227–242. https://doi.org/10.1145/1640089.1640106
[18] Josep M Perez, Rosa M Badia, and Jesus Labarta. 2008. A dependency-aware task-based programming environment for multi-core architectures. In 2008 IEEE International Conference on Cluster Computing. IEEE, 142–151.
[19] A. Robison, M. Voss, and A. Kukanov. 2008. Optimization via Reflection on Work Stealing in TBB. In 2008 IEEE International Symposium on Parallel and Distributed Processing. 1–8.
[20] Shumpei Shiina and Kenjiro Taura. 2019. Almost Deterministic Work Stealing. In Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis (Denver, Colorado) (SC ’19). Association for Computing Machinery, New York, NY, USA, Article 47, 16 pages. https://doi.org/10.1145/3295500.3356161
[21] Marc Tchiboukdjian, Nicolas Gast, Denis Trystram, Jean-Louis Roch, and Julien Bernard. 2010. A Tighter Analysis of Work Stealing. In Algorithms and Computation, Offried Cheong, Kyung-Yong Chwa, and Kunsoo Park (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 291–302.
[22] Peter Thoman, Kiril Dichev, Thomas Heller, Roman Iakymchuk, Xavier Aguilar, Khalid Hasanov, Philipp Gschwandtner, Pierre Lemarinier, Stefan Markidis, Herbert Jordan, et al. 2018. A taxonomy of task-based parallel programming technologies for high-performance computing. The Journal of Supercomputing 74, 4 (2018), 1422–1434.
[23] Afshin Zafari, Elisabeth Larsson, and Martin Tillenius. 2019. DuctTeip: An efficient programming model for distributed task-based parallel computing. Parallel Comput. 90 (2019), 102582. https://doi.org/10.1016/j.parco.2019.102582