

# *Arrows for Parallel Computations*

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## Abstract

Arrows are a general interface for computation and therefore form an alternative to Monads for API design. We express parallelism using this concept in a novel way: We define an Arrow-based language for parallelism and implement it using multiple parallel Haskell. In this manner we are able to bridge across various parallel Haskell.

Additionally, using these parallel Arrows (PArrows) has the benefit of being portable across multiple parallel Haskell implementations. Furthermore, as each parallel computation is an Arrow, PArrows can be readily composed and transformed as such. In order to allow for more sophisticated communication schemes between computation nodes in distributed systems we utilise the concept of Futures to wrap existing direct communication concepts in backends.

To show that PArrows have similar expressive power as existing parallel languages, we also implement several parallel skeletons. Benchmarks show that our framework does not induce any notable overhead performance-wise. We finally conclude that Arrows turn out to be a useful tool for composing parallel programs and that our particular approach results in programs that are portable across multiple backends. **OL: Summarize conclusions**

**MB: Jedes Kapitel soll einmal ins Abstract. Conclusions sollen mit ins Abstract**

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## Contents

<b>1</b>	<b>Introduction</b>	2
<b>2</b>	<b>Related Work</b>	3
<b>3</b>	<b>Background</b>	5
3.1	Arrows	5
3.2	Short introduction to parallel Haskell	7
<b>4</b>	<b>Parallel Arrows</b>	10
4.1	The ArrowParallel type class	10
4.2	ArrowParallel instances	11
4.3	Extending the Interface	13
<b>5</b>	<b>Futures</b>	14
<b>6</b>	<b>Skeletons</b>	16
6.1	map-based Skeletons	16
6.2	Topological Skeletons	17

<b>7 Performance results and discussion</b>	23
7.1 Preliminaries	24
7.2 Benchmark results	27
7.3 Discussion	29
<b>8 Conclusion</b>	30
8.1 Future Work	30
<b>A Utility Arrows</b>	35
<b>B Profunctor Arrows</b>	36
<b>C Omitted Function Definitions</b>	36
<b>D Syntactic Sugar</b>	37

## 1 Introduction

Parallel functional languages have a long history of being used for experimenting with novel parallel programming paradigms including the expression of parallelism. Haskell, which we focus on in this paper, has several mature implementations. We regard here in-depth Glasgow parallel Haskell or short GpH (its Multicore SMP implementation, in particular), the *Par* Monad, and Eden, a distributed memory parallel Haskell. These languages represent orthogonal approaches. Some use a monad, even if only for the internal representation. Some introduce additional language constructs. Section 3.2 gives a short overview over these languages.

A key novelty in this paper is to use Arrows to represent parallel computations. They seem a natural fit as they can be thought of as a more general function arrow ( $\rightarrow$ ) and serve as general interface to computations while not being as restrictive as Monads (Hughes, 2000). Section 3.1 gives a short introduction to Arrows.

We provide an Arrows-based type class and implementations for the three above mentioned parallel Haskell. Instead of introducing a new low-level parallel backend in order to implement our Arrows-based interface, we define a shallow-embedded DSL for Arrows. This DSL is defined as a common interface with varying implementations in the existing parallel Haskell. Thus, we not only define a parallel programming interface in a novel manner – we tame the zoo of parallel Haskell. We provide a common, very low-penalty programming interface that allows to switch the parallel backends at will. The induced penalty was max. 8.3 % in our measurements **MB: , and typically under X %**. Further backends based on HdpH or a Frege implementation (on the Java Virtual Machine) are viable, too.

**Contributions** We propose an Arrow-based encoding for parallelism based on a new Arrow combinator  $parEvalN :: [arr\ a\ b] \rightarrow arr\ [a]\ [b]$ . A parallel Arrow is still an Arrow, hence the resulting parallel Arrow can still be used in the same way as a potential sequential version. In this paper we evaluate the expressive power of such a formalism in the context of parallel programming.

We structure this paper as follows:

- We introduce a parallel evaluation formalism using Arrows. One big advantage of our specific approach is that we do not have to introduce any new types (Sec. 4). This behaviour encourages better composability.
- We utilize multiple backends – currently a GpH, a *Par* Monad, and Eden. We do not reimplement all the parallel internals, as we host this functionality in the *ArrowParallel* type class, which abstracts all parallel implementation logic. The backends can easily be swapped, so we are not bound to any specific one. So as an example, during development, we can run the program in a simple GHC-compiled variant using a GpH backend and afterwards deploy it on a cluster by converting it into an Eden program, by just replacing the *ArrowParallel* instance and compiling with Eden’s GHC variant. (Sec. 4)
- We extend our PArrows formalism with *Futures*. Our goal here is to enable direct communication of data between nodes in a distributed memory setting similar to Eden’s Remote Data (*RD*). Direct communication is useful in a distributed memory setting because it allows for inter-node communication without blocking the master-node. (Sec. 5)
- It is possible to define algorithmic skeletons with PArrows (Sec. 6). All our benchmarks were skeleton-based.
- Finally, we practically demonstrate that Arrow parallelism is a viable alternative to existing approaches. It introduces only low performance overhead (Sec. 7).

PArrows are open source and available from <https://github.com/s4ke/Parrows>.

## 2 Related Work

**Parallel Haskell.** Of course, the three parallel Haskell flavours we use as backends: the GpH (Trinder *et al.*, 1996, 1998) parallel Haskell dialect and its multicore version (Marlow *et al.*, 2009), the *Par* Monad (Marlow *et al.*, 2011; Foltzer *et al.*, 2012), and Eden (Loogen *et al.*, 2005; Loogen, 2012) are related to this work. We use these languages as backends: our DSL can switch from one to other at user’s command.

HdpH (Maier *et al.*, 2014; Stewart *et al.*, 2016) is an extension of *Par* Monad to heterogeneous clusters. LVish (Kuper *et al.*, 2014) is a communication-centred extension of *Par* Monad. Further parallel Haskell approaches include pH (Nikhil & Arvind, 2001), research work done on distributed variants of GpH (Trinder *et al.*, 1996; Aljabri *et al.*, 2014, 2015), and low-level Eden implementation (Berthold, 2008; Berthold *et al.*, 2016). Skeleton composition (Dieterle *et al.*, 2016), communication (Dieterle *et al.*, 2010a), and generation of process networks (Horstmeyer & Loogen, 2013) are recent in-focus research topics in Eden. This also includes the definitions of new skeletons (Hammond *et al.*, 2003; Berthold & Loogen, 2006; Berthold *et al.*, 2009b,c; Dieterle *et al.*, 2010b; de la Encina *et al.*, 2011; Dieterle *et al.*, 2013; Janjic *et al.*, 2013).

More different approaches include data parallelism (Chakravarty *et al.*, 2007; Keller *et al.*, 2010), GPU-based approaches (Mainland & Morrisett, 2010; Svensson, 2011), software transactional memory (Harris *et al.*, 2005; Perfumo *et al.*, 2008). The Haskell–GPU bridge Accelerate (Chakravarty *et al.*, 2011; Clifton-Everest *et al.*, 2014; McDonell *et al.*, 2015) deserves a special mention. Accelerate is completely orthogonal to our approach. Marlow authored a recent book in 2013 on parallel Haskell.

**Algorithmic skeletons.** Algorithmic skeletons were introduced by Cole (1989). Early publications on this topic include (Darlington *et al.*, 1993; Botorog & Kuchen, 1996; Danelutto *et al.*, 1997; Gorlatch, 1998; Lengauer *et al.*, 1997). Rabhi & Gorlatch (2003) consolidated early reports on high-level programming approaches. The effort is ongoing, including topological skeletons (Berthold & Loogen, 2006), special-purpose skeletons for computer algebra (Berthold *et al.*, 2009c; Lobachev, 2011, 2012; Janjic *et al.*, 2013), iteration skeletons (Dieterle *et al.*, 2013). The idea of Linton *et al.* (2010) is to use a parallel Haskell to orchestrate further software systems to run in parallel. Dieterle *et al.* (2016) compare the composition of skeletons to stable process networks.

**Arrows.** Arrows were introduced by Hughes (2000) as a less restrictive alternative to Monads, basically they are a generalised function arrow  $\rightarrow$ . Hughes (2005a) presents a tutorial on Arrows. Some theoretical details on Arrows (Jacobs *et al.*, 2009; Lindley *et al.*, 2011; Atkey, 2011) are viable. Paterson (2001) introduced a new notation for Arrows. Arrows have applications in information flow research (Li & Zdancewic, 2006, 2010; Russo *et al.*, 2008), invertible programming (Alimarine *et al.*, 2005), and quantum computer simulation (Vizzotto *et al.*, 2006). But probably most prominent application of Arrows is Arrow-based functional reactive programming, AFRP (Nilsson *et al.*, 2002; Hudak *et al.*, 2003; Czaplicki & Chong, 2013). Liu *et al.* (2009) formally define a more special kind of Arrows that capsule the computation more than regular arrows do and thus enable optimizations. Their approach would allow parallel composition, as their special Arrows would not interfere with each other in concurrent execution. In contrast, we capture a whole parallel computation as a single entity: our main instantiation function *parEvalN* makes a single (parallel) Arrow out of list of Arrows. Huang *et al.* (2007) utilise Arrows for parallelism, but strikingly different from our approach. They use Arrows to orchestrate several tasks in robotics. We, however, propose a general interface for parallel programming, while remaining completely in Haskell.

**Other languages.** Although this work is centered on Haskell implementation of Arrows, it is applicable to any functional programming language where parallel evaluation and Arrows can be defined. Experiments with our approach in Frege language<sup>1</sup> (which is basically Haskell on the JVM) were quite successful. A new approach to Haskell on the JVM is the Eta language<sup>2</sup>. However, both are beyond the scope of this work.

Achten *et al.* (2004, 2007) use an Arrow implementation in Clean for better handling of typical GUI tasks. Dagand *et al.* (2009) used Arrows in OCaml in the implementation of a distributed system.

<sup>1</sup> GitHub project page at <https://github.com/Frege/frege>

<sup>2</sup> Eta project page at [eta-lang.org](http://eta-lang.org)

```

class Arrow arr where
  arr :: (a → b) → arr a b
  (>>>) :: arr a b → arr b c → arr a c
  first :: arr a b → arr (a, c) (b, c)

instance Arrow (→) where
  arr f = f
  f >>> g = g ∘ f
  first f = λ(a, c) → (f a, c)

data Kleisli m a b = Kleisli { run :: a → m b }

instance Monad m ⇒ Arrow (Kleisli m) where
  arr f = Kleisli (return ∘ f)
  f >>> g = Kleisli (λa → f a >>= g)
  first f = Kleisli (λ(a, c) → f a >>= λb → return (b, c))

```

Figure 1: The definition of the Arrow type class and its two most typical instances.

### 3 Background

#### 3.1 Arrows

Arrows were introduced by Hughes (2000) as a general interface for computation and a less restrictive generalisation of Monads. Hughes motivates the broader interface of Arrows with the example of a parser with added static meta-information that can not satisfy the monadic bind operator ( $\gg$ ) ::  $m\ a \rightarrow (a \rightarrow m\ b) \rightarrow m\ b$  (with  $m$  being a Monad). In the example a parser of the type *Parser*  $s\ a$  with static meta information  $s$  and result  $a$  is shown to not be able to use the static information  $s$  without applying the monadic function  $a \rightarrow m\ b$ . With Arrows this is possible.

An Arrow *arr*  $a\ b$  represents a computation that converts an input  $a$  to an output  $b$ . This is defined in the Arrow type class shown in Fig. 1. To lift an ordinary function to an Arrow, *arr* is used, analogous to the monadic *return*. Similarly, the composition operator  $\gg$  is analogous to the monadic composition  $\gg$  and combines two arrows *arr*  $a\ b$  and *arr*  $b\ c$  by ‘wiring’ the outputs of the first to the inputs to the second to get a new arrow *arr*  $a\ c$ . Lastly, the *first* operator takes the input Arrow *arr*  $a\ b$  and converts it into an arrow on pairs *arr* ( $a, c$ ) ( $b, c$ ) that leaves the second argument untouched. It allows us to save input across arrows. Figure 2 shows a graphical representation of these basic Arrow combinators. The most prominent instances of this interface are regular functions (→) and the Kleisli type (Fig. 1), which wraps monadic functions, e.g.  $a \rightarrow m\ b$ .

Hughes also defined some syntactic sugar (Fig. 3): *second*, *\*\*\** and *&&&*. *second* is the mirrored version of *first* (Appendix A). *\*\*\** combines *first* and *second* to handle two inputs in one arrow, and is defined as follows:

```

(***) :: Arrow arr ⇒ arr a b → arr c d → arr (a, c) (b, d)
f *** g = first f >>> second g

```

The *&&&* combinator, which constructs an Arrow that outputs two different values like *\*\*\**, but takes only one input, is:

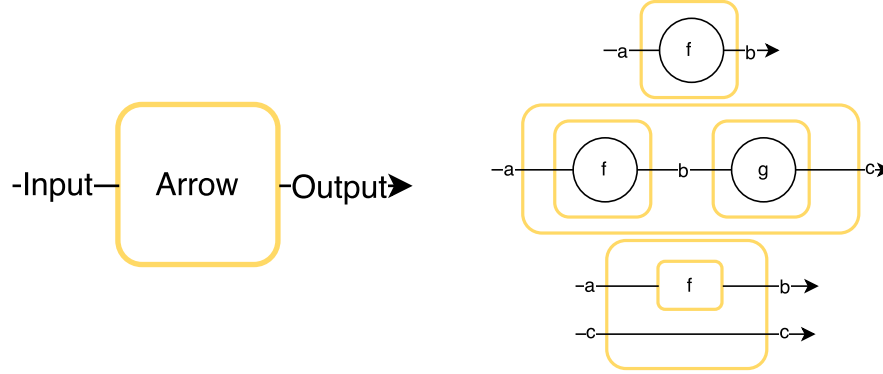


Figure 2: Schematic depiction of an Arrow (left) and its basic combinators *arr*, *>>>* and *first* (right).

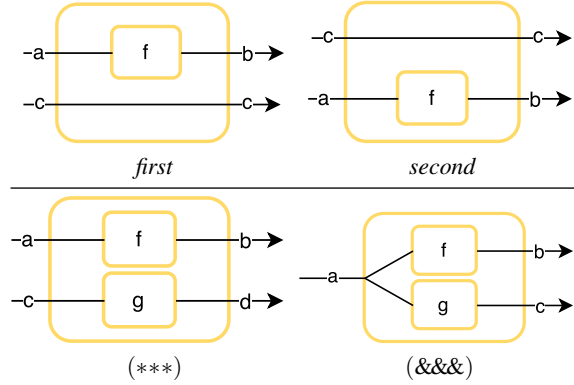


Figure 3: Visual depiction of syntactic sugar for Arrows.

$$\begin{aligned}
 (&\&\&) :: \text{Arrow } arr \Rightarrow arr\ a\ b \rightarrow arr\ a\ c \rightarrow arr\ a\ (b, c) \\
 f\ \&\&\&\ g &= arr\ (\lambda a \rightarrow (a, a))\ >>>\ (f\ ***\ g)
 \end{aligned}$$

A first short example given by Hughes on how to use arrows is addition with arrows:

$$\begin{aligned}
 add &:: \text{Arrow } arr \Rightarrow arr\ a\ Int \rightarrow arr\ a\ Int \rightarrow arr\ a\ Int \\
 add\ f\ g &= (f\ \&\&\&\ g)\ >>>\ arr\ (\lambda (u, v) \rightarrow u + v)
 \end{aligned}$$

As we can rewrite the monadic bind operation ( $\gg=$ ) with only the Kleisli type into  $m\ a \rightarrow \text{Kleisli } m\ a\ b \rightarrow m\ b$ , but not with a general  $\text{Arrow } arr\ a\ b$ , we can intuitively get an idea of why Arrows must be a generalisation of Monads. While this also means that a general Arrow can not express everything a Monad can, the Parser example shows that this trade-off is worth it in some cases.

In this paper we will show that we can express parallel computations with Arrows and do not require Monads to do so. We also do not restrict the compatible Arrows to ones which have *ArrowApply* instances but instead only require instances for *ArrowChoice* and

## Arrows for Parallel Computations

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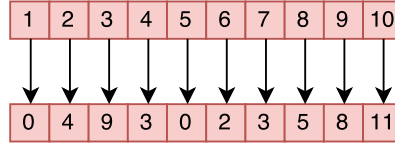


Figure 4: Schematic illustration of *parEvalN*. A list of inputs is transformed by different functions in parallel.

*ArrowLoop*. Because of this, we have a truly more general interface as compared to a monadic one.

Also note that, while we could have based our DSL on Profunctors as well, we chose Arrows **MB: cite missing?** for this paper since they allow for a more direct way of thinking about parallelism than general Profunctors because of their composability. However, they are a promising candidate for future improvements of our DSL. Note that some Profunctors, especially ones supporting a composition operation among other things, can already be adapted to our interface as shown in Appendix B.

### 3.2 Short introduction to parallel Haskell

In its purest form, parallel computation (on functions) can be looked at as the execution of some functions  $a \rightarrow b$  in parallel or  $\text{parEvalN} :: [a \rightarrow b] \rightarrow [a] \rightarrow [b]$ , as also Figure 4 symbolically shows.

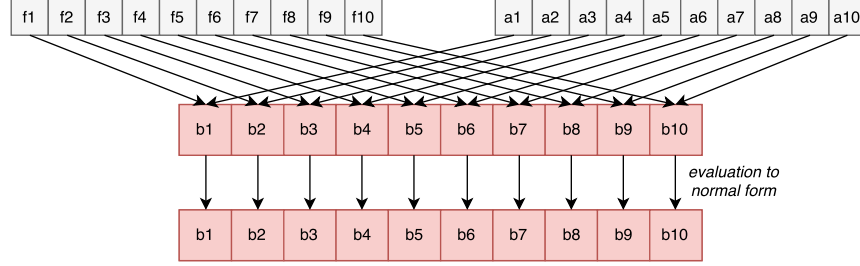
In this section, we will implement this non-Arrow version which will later be adapted for usage in our Arrow-based parallel Haskell.

There exist several parallel Haskell already. Among the most important are probably GpH (based on *par* & *pseq* ‘hints’) (Trinder *et al.*, 1996, 1998), the *Par* Monad (a monad for deterministic parallelism) (Marlow *et al.*, 2011; Foltzer *et al.*, 2012), Eden (a parallel Haskell for distributed memory) (Loogen *et al.*, 2005; Loogen, 2012), HdpH (a Template Haskell based parallel Haskell for distributed memory) (Maier *et al.*, 2014; Stewart *et al.*, 2016) and LVish (a *Par* extension with focus on communication) (Kuper *et al.*, 2014).

As the goal of this paper is not to reimplement yet another parallel runtime, but to represent parallelism with Arrows, we base our efforts on existing work which we wrap as backends behind a common interface. For this paper we chose GpH for its simplicity, the *Par* Monad to represent a monadic DSL, and Eden as a distributed parallel Haskell.

LVish and HdpH were not chosen as the former does not differ from the original *Par* Monad with regard to how we would have used it in this paper, while the latter (at least in its current form) does not comply with our representation of parallelism due to its heavy reliance on TemplateHaskell.

We will now go into some detail on GpH, the *Par* Monad and Eden, and also give their respective implementations of the non-Arrow version of *parEvalN*.

Figure 5: Data flow of the GpH *parEvalN* version.

### 3.2.1 Glasgow parallel Haskell – GpH

GpH (Marlow *et al.*, 2009; Trinder *et al.*, 1998) is one of the simplest ways to do parallel processing found in standard GHC.<sup>3</sup> Besides some basic primitives (*par* & *pseq* hints), it ships with parallel evaluation strategies for several types which can be applied with *using*  $:: a \rightarrow \text{Strategy } a \rightarrow a$ , which is exactly what is required for an implementation of *parEvalN*.

```
parEvalN :: (NFData b) => [a -> b] -> [a] -> [b]
parEvalN fs as = let bs = zipWith ($) fs as
               in bs 'using' parList rdeepseq
```

In the above definition of *parEvalN* we just apply the list of functions  $[a \rightarrow b]$  to the list of inputs  $[a]$  by zipping them with the application operator  $\$$ . We then evaluate this lazy list  $[b]$  according to a *Strategy*  $[b]$  with the *using*  $:: a \rightarrow \text{Strategy } a \rightarrow a$  operator. We construct this strategy with *parList*  $:: \text{Strategy } a \rightarrow \text{Strategy } [a]$  and *rdeepseq*  $:: \text{NFData } a \Rightarrow \text{Strategy } a$  where the latter is a strategy which evaluates to normal form. Fig. 5 shows a visual representation of this code.

### 3.2.2 Par Monad

The *Par* Monad<sup>4</sup> introduced by Marlow *et al.* (2011), is a Monad designed for composition of parallel programs. Let:

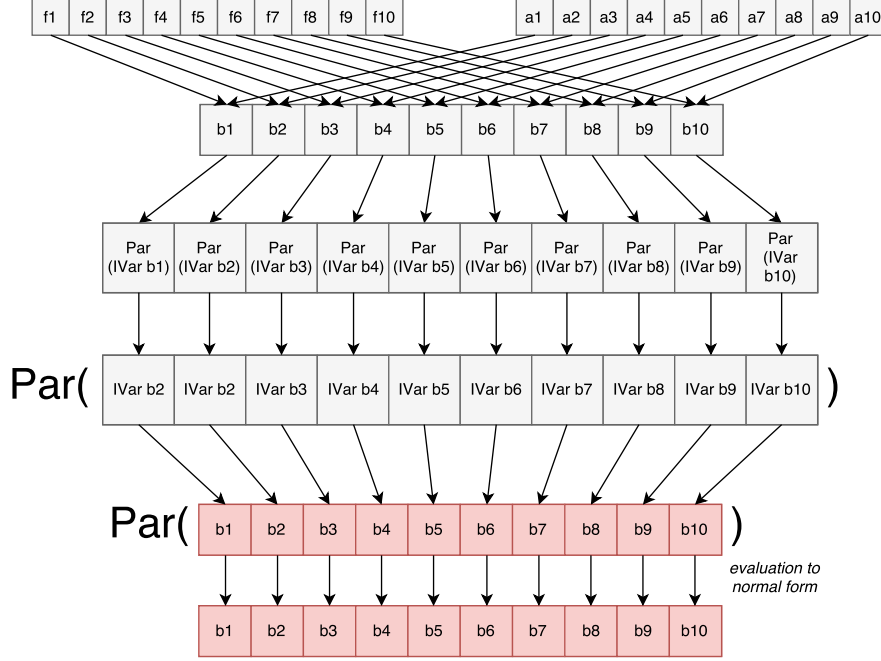
```
parEvalN :: (NFData b) => [a -> b] -> [a] -> [b]
parEvalN fs as = runPar $
  (sequenceA (map (return o spawn) (zipWith ($) fs as))) >>= mapM get
```

The *Par* Monad version of our parallel evaluation function *parEvalN* is defined by zipping the list of  $[a \rightarrow b]$  with the list of inputs  $[a]$  with the application operator  $\$$  just like with GpH. Then, we map over this not yet evaluated lazy list of results  $[b]$  with *spawn*  $:: \text{NFData } a \Rightarrow \text{Par } a \rightarrow \text{Par } (\text{IVar } a)$  to transform them to a list of not yet evaluated

<sup>3</sup> The Multicore implementation of GpH is available on Hackage under <https://hackage.haskell.org/package/parallel-3.2.1.0>, compiler support is integrated in the stock GHC.

<sup>4</sup> The *Par* monad can be found in the *monad-par* package on Hackage under <https://hackage.haskell.org/package/monad-par-0.3.4.8/>.



Figure 6: Data flow of the *Par* Monad *parEvalN* version.

forked away computations  $[Par (IVar b)]$ , which we convert to  $Par [IVar b]$  with *sequenceA*. We wait for the computations to finish by mapping over the *IVar b* values inside the *Par* Monad with *get*. This results in  $Par [b]$ . We execute this process with *runPar* to finally get  $[b]$ . While we used *spawn* in the definition above, a head-strict variant can easily be defined by replacing *spawn* with *spawn\_* ::  $Par a \rightarrow Par (IVar a)$ . Fig. 6 shows a graphical representation.

### 3.2.3 Eden

Eden (Loogen *et al.*, 2005; Loogen, 2012) is a parallel Haskell for distributed memory and comes with a MPI and a PVM backends.<sup>5</sup> It is targeted towards clusters, but also functions well in a shared-memory setting with a further simple backend. However, in contrast to many other parallel Haskell, in Eden each process has its own heap. This seems to be a waste of memory, but with distributed programming paradigm and individual GC per process, Eden yields good performance results on multicores, as well (Berthold *et al.*, 2009a; Aswad *et al.*, 2009).

While Eden comes with a Monad *PA* for parallel evaluation, it also ships with a completely functional interface that includes a *spawnF* ::  $(Trans\ a, Trans\ b) \Rightarrow [a \rightarrow b] \rightarrow [a] \rightarrow [b]$  function that allows us to define *parEvalN* directly:

<sup>5</sup> The projects homepage can be found at <http://www.mathematik.uni-marburg.de/~eden/>. The Hackage page is at <https://hackage.haskell.org/package/edenmodules-1.2.0.0/>.

$$\begin{aligned} \text{parEvalN} &:: (\text{Trans } a, \text{Trans } b) \Rightarrow [a \rightarrow b] \rightarrow [a] \rightarrow [b] \\ \text{parEvalN} &= \text{spawnF} \end{aligned}$$

**Eden TraceViewer.** To comprehend the efficiency and the lack thereof in a parallel program, an inspection of its execution is extremely helpful. While some large-scale solutions exist (Geimer *et al.*, 2010), the parallel Haskell community mainly utilises the tools Threadscope (Wheeler & Thain, 2009) and Eden TraceViewer<sup>6</sup> (Berthold & Loogen, 2007). In the next sections we will present some *trace visualizations*, the post-mortem process diagrams of Eden processes and their activity.

The trace visualizations are color-coded. In such a visualization (Fig. 12), the  $x$  axis shows the time, the  $y$  axis enumerates the machines and processes. The visualization shows a running process in green, a blocked process is red. If the process is ‘runnable’, i.e. it may run, but does not, it is yellow. The typical reason for this is GC. An inactive machine, where no processes are started yet, or all are already terminated, shows as a blue bar. A communication from one process to another is represented with a black arrow. A stream of communications, e.g. a transmitted list is shown as a dark shading between sender and receiver processes.

## 4 Parallel Arrows

Arrows are a general interface to computation. Here we introduce special Arrows as general interface to *parallel computations*. First, we present the interface and explain the reasonings behind it. Then, we discuss some implementations using existing parallel Haskell. Finally, we explain why using Arrows for expressing parallelism is beneficial.

### 4.1 The ArrowParallel type class

A parallel computation (on functions) in its purest form can be seen as execution of some functions  $a \rightarrow b$  in parallel, as our *parEvalN* prototype shows (Sec. 3.2). Translating this into arrow terms gives us a new operator *parEvalN* that lifts a list of arrows  $[arr\ a\ b]$  to a parallel arrow  $arr\ [a]\ [b]$ . This combinator is similar to our utility function *evalN* from Appendix A, but does parallel instead of serial evaluation.

$$\text{parEvalN} :: (\text{Arrow } arr) \Rightarrow [arr\ a\ b] \rightarrow arr\ [a]\ [b]$$

With this definition of *parEvalN*, parallel execution is yet another arrow combinator. But as the implementation may differ depending on the actual type of the arrow *arr* and we want this to be an interface for different backends, we introduce a new type class *ArrowParallel* *arr a b*:

```
class Arrow arr  $\Rightarrow$  ArrowParallel arr a b where
  parEvalN :: [arr a b]  $\rightarrow$  arr [a] [b]
```

<sup>6</sup> See <http://hackage.haskell.org/package/edentv> on Hackage for the last available version of Eden TraceViewer.

```

data Conf a = Conf (Strategy a)
instance (NFData b, ArrowChoice arr) =>
  ArrowParallel arr a b (Conf b) where
    parEvalN (Conf strat) fs =
      evalN fs >>>
      arr (withStrategy (parList strat))

```

Figure 7: The *ArrowParallel* instance for the GpH backend.

Sometimes parallel Haskell's require or allow for additional configuration parameters, e. g. an information about the execution environment or the level of evaluation (weak head normal form vs. normal form). For this reason we also introduce an additional *conf* parameter to the function. We also do not want *conf* to be a fixed type, as the configuration parameters can differ for different instances of *ArrowParallel*.

```

class Arrow arr => ArrowParallel arr a b conf where
  parEvalN :: conf -> [arr a b] -> arr [a] [b]

```

## 4.2 ArrowParallel instances

### 4.2.1 Glasgow parallel Haskell

The GpH implementation of *ArrowParallel* is implemented in a straightforward manner in Fig. 7, but a bit different compared to the variant from Section 3.2.1, by using *evalN* ::  $[arr\ a\ b] \rightarrow arr\ [a]\ [b]$  (definition in Appendix A, think *zipWith* (\$) on Arrows) combined with *withStrategy* :: *Strategy* *a* -> *a* -> *a* from GpH, where *withStrategy* is the same as *using* :: *a* -> *Strategy* *a* -> *a*, but with flipped parameters. Our *Conf a* datatype simply wraps a *Strategy a*, but could be extended in future versions of our DSL.

### 4.2.2 Par Monad

**OL: introduce a newcommand for par-monad, "arrows", "parrows" and replace all mentions to them to ensure uniform typesetting done!, we write Arrows. also "Monad"? done!** Just like for GpH we can easily lift the definition of *parEvalN* for the *Par* Monad to Arrows in Fig. 8. To start off, we define the *Strategy a* and *Conf a* type so we can have a configurable instance of *ArrowParallel*:

```

type Strategy a = a -> Par (IVar a)
data Conf a = Conf (Strategy a)

```

Now we can once again define our *ArrowParallel* instance as follows: First, we convert our Arrows  $[arr\ a\ b]$  with *evalN* (*map* ( $\gg\gg\gg arr\ strat$ ) *fs*) into an Arrow *arr*  $[a]\ [(Par\ (IVar\ b))]$  that yields composable computations in the *Par* monad, where *evalN* is once again of the type *evalN* ::  $[arr\ a\ b] \rightarrow arr\ [a]\ [b]$ . By combining the result of this Arrow with *arr sequenceA*, we get an Arrow *arr*  $[a]\ (Par\ [IVar\ b])$ . Then, in order to fetch the results of the different threads, we map over the *IVars* inside the *Par* Monad with *arr* ( $\gg\gg mapM\ get$ )

- our intermediary Arrow is of type  $\text{arr } [a] \text{ (Par } [b])$ . Finally, we execute the computation  $\text{Par } [b]$  by composing with  $\text{arr runPar}$  and get the final Arrow  $\text{arr } [a] [b]$ .

```
instance (NFData b, ArrowChoice arr)  $\Rightarrow$  ArrowParallel arr a b (Conf b) where
  parEvalN (Conf strat) fs = evalN (map (>>> arr strat) fs) >>>
    arr sequenceA >>>
    arr (>>= mapM Control.Monad.Par.get) >>>
    arr runPar
```

Figure 8: ArrowParallel instance for the Par Monad backend.

#### 4.2.3 Eden

For both the GpH Haskell and *Par* Monad implementations we could use general instances of *ArrowParallel* that just require the *ArrowChoice* type class. With Eden this is not the case as we can only spawn a list of functions, which we cannot extract from general arrows. While we could still manage to have only one instance in the module by introducing a type class

```
class (Arrow arr)  $\Rightarrow$  ArrowUnwrap arr where
  arr a b  $\rightarrow$  (a  $\rightarrow$  b)
```

, we avoid doing so for aesthetic reasons. For now, we just implement *ArrowParallel* for normal functions:

```
instance (Trans a, Trans b)  $\Rightarrow$  ArrowParallel ( $\rightarrow$ ) a b Conf where
  parEvalN _ = spawnF
```

and the Kleisli type:

```
instance (ArrowParallel ( $\rightarrow$ ) a (m b) Conf,
  Monad m, Trans a, Trans b, Trans (m b))  $\Rightarrow$ 
  ArrowParallel (Kleisli m) a b conf where
  parEvalN conf fs = arr (parEvalN conf (map ( $\lambda$  (Kleisli f)  $\rightarrow$  f) fs)) >>>
    Kleisli sequence
```

where *Conf* is simply defined as **data** *Conf* = *Nil* since Eden does not have a configurable *spawnF* variant.

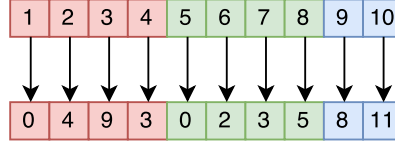
#### 4.2.4 Default configuration instances

While the configurability in the instances of the *ArrowParallel* instances above is nice, users probably would like to have a proper default configuration for many parallel programs as well. These can also easily be defined as we can see by the example of the default implementation of *ArrowParallel* for the GpH backend:

```
instance (NFData b, ArrowChoice arr, ArrowParallel arr a b (Conf b))  $\Rightarrow$ 
  ArrowParallel arr a b () where
```

## Arrows for Parallel Computations

13

Figure 9: Schematic depiction of *parEvalNLazy*.

```

parEvalN _fs = parEvalN (defaultConf fs) fs
defaultConf :: (NFData b) => [arr a b] -> Conf b
defaultConf fs = stratToConf fs rdeepseq
stratToConf :: [arr a b] -> Strategy b -> Conf b
stratToConf _ strat = Conf strat

```

The other backends have similarly structured implementations which we do not discuss here for brevity reasons. Note that by restricting the original implementations of our backends to their specific *Conf* type, we also get interoperability between backends for free. We can parallelize one part of a program using one backend, and parallelize the next with another one. We can however only have one instance of *ArrowParallel arr a b ()* present at a time.

Up until now we discussed Arrow operations more in detail, but in the following sections we focus more on the dataflow between the arrows, now that we have seen that Arrows are capable of expressing parallelism. We do however explain new concepts with more details if required for easier understanding.

### 4.3 Extending the Interface

With the *ArrowParallel* type class in place and implemented, we can now implement some further basic parallel interface functions. These are algorithmic skeletons that, however, mostly serve as a foundation to further, more specific algorithmic skeletons.

#### 4.3.1 Lazy *parEvalN*

The function *parEvalN* is 100% strict, which means that it fully evaluates all passed arrows. Sometimes this might not be feasible, as it will not work on infinite lists of functions like e.g. `map (arr ∘ (+)) [1..]` or just because we need the arrows evaluated in chunks. *parEvalNLazy* (Figs. 9, 10) fixes this. It works by first chunking the input from `[a]` to `[[a]]` with the given *ChunkSize* in `arr (chunksOf chunkSize)`. These chunks are then fed into a list `[arr [a] [b]]` of parallel arrows created by feeding chunks of the passed *ChunkSize* into the regular *parEvalN* by using `listApp`. The resulting `[[b]]` is lastly converted into `[b]` with `arr concat`.

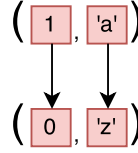
#### 4.3.2 Heterogeneous tasks

We have only talked about the parallelisation of arrows of the same type until now. But sometimes we want to parallelize heterogeneous types as well. We can implement such a

```

parEvalNLazy :: (ArrowParallel arr a b conf, ArrowChoice arr, ArrowApply arr) =>
  conf -> ChunkSize -> [arr a b] -> (arr [a] [b])
parEvalNLazy conf chunkSize fs =
  arr (chunksOf chunkSize) >>>
  evalN fchunks >>>
  arr concat
where
  fchunks = map (parEvalN conf) (chunksOf chunkSize fs)

```

Figure 10: Definition of *parEvalNLazy*.Figure 11: Schematic depiction of *parEval2*.

*parEval2* combinator (Figs. 11, C 12) which combines two arrows *arr a b* and *arr c d* into a new parallel arrow *arr (a, c) (b, d)* quite easily with the help of the *ArrowChoice* type class. The idea is to use the *+++* combinator which combines two arrows *arr a b* and *arr c d* and transforms them into *arr (Either a c) (Either b d)* to get a common arrow type that we can then feed into *parEvalN*.

## 5 Futures

Consider a mock-up parallel Arrow combinator:

```

someCombinator :: (ArrowChoice arr,
  ArrowParallel arr a b (),
  ArrowParallel arr b c ()) =>
  [arr a b] -> [arr b c] -> arr [a] [c]
someCombinator fs1 fs2 =
  parEvalN ().fs1 >>>
  rightRotate >>>
  parEvalN ().fs2

```

In a distributed environment, a resulting arrow of this combinator first evaluates all *[arr a b]* in parallel, sends the results back to the master node, rotates the input once (in the example we require *ArrowChoice* for this) and then evaluates the *[arr b c]* in parallel to then gather the input once again on the master node. Such situations arise, e.g. in scientific computations when the data distributed across the nodes needs to be transposed. A concrete example is 2D FFT computation (Gorlatch & Bischof, 1998; Berthold *et al.*, 2009c).

While the above example could be rewritten into only one *parEvalN* call by directly wiring the arrows together before spawning, it illustrates an important problem. When using a *ArrowParallel* backend that resides on multiple computers, all communication between

the nodes is done via the master node, as shown in the Eden trace in Figure 12. This can become a serious bottleneck for larger amount of data and number of processes (as e.g. Berthold *et al.*, 2009c, showcases).

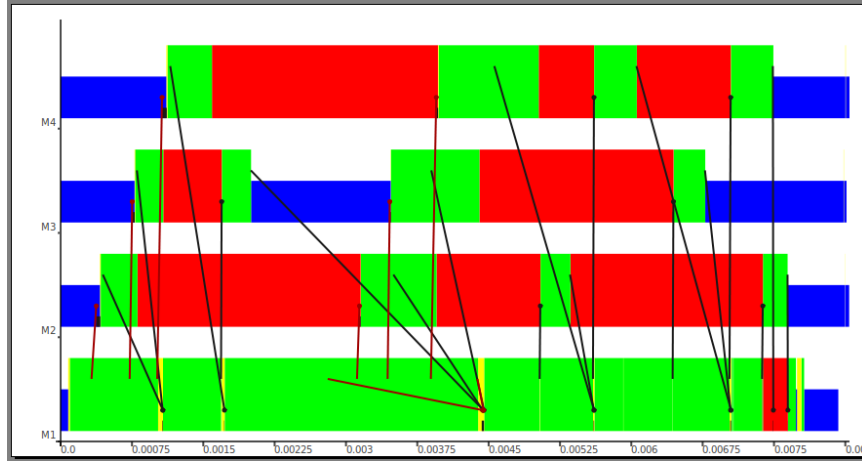


Figure 12: Communication between 4 Eden processes without Futures. All communication goes through the master node. Each bar represents one process. Black lines between processes represent communication. Colors: blue  $\hat{=}$  idle, green  $\hat{=}$  running, red  $\hat{=}$  blocked, yellow  $\hat{=}$  suspended.

**OL:** more practical and heavy-weight example! fft (I have the code)?

**MB:** Depends... Are the communications easy to read in such an example?

**MB:** Keep the description for the different colours, or link to the EdenTV description in 3.2.3

**OL:** ok as is **OL:** use the fft example (when it works)?

This is in fact only a problem in distributed memory (in the scope of this paper) and we should allow nodes to communicate directly with each other. Eden already ships with ‘remote data’ that enable this (Alt & Gorlatch, 2003; Dieterle *et al.*, 2010a). But as we want code with our DSL to be implementation agnostic, we have to wrap this concept. We do this with the *Future* type class (Fig. 13). Note that we require a *conf* parameter here as well, but only so that Haskell’s type system allows us to have multiple *Future* implementations imported at once without breaking any dependencies similar to what we did with the *ArrowParallel* typeclass earlier. Since *RD* is only a type synonym for a communication type

```
class Future fut a conf | a conf -> fut where
  put :: (Arrow arr) => conf -> arr a (fut a)
  get :: (Arrow arr) => conf -> arr (fut a) a
```

Figure 13: Definition of the *Future* type class.

that Eden uses internally, we have to use some wrapper classes to fit that definition, though, as Fig. C 1 shows. Technical details are in Appendix, in Section C.

For the *Par* Monad and GpH Haskell backends, we can simply use *BasicFutures* (Fig. C 2), which are just simple wrappers around the actual data with boiler-plate logic so that the type class is satisfied. This is because the concept of a *Future* does not change anything for shared-memory execution as there are no communication problems to fix. Nevertheless, we require a common interface so the parallel Arrows are portable across backends. The implementation can also be found in Section C.

In our communication example we can use this *Future* concept for direct communication between nodes as shown in Fig. 14. Note that with our PArrows DSL we can also define default instances *Future fut a ()* for each backend similar to how *ArrowParallel arr a b ()* was defined in Section 4. Details can be found in Section C. In a distributed environment,

```
someCombinator :: (ArrowChoice arr, NFData b, NFData c,
  ArrowParallel arr a (fut b) (),
  ArrowParallel arr (fut b) c (),
  Future fut b ()) =>
  [arr a b] -> [arr b c] -> arr [a] [c]
someCombinator fs1 fs2 =
  parEvalN () (map (>>>put ()) fs1) >>>
  rightRotate >>>
  parEvalN () (map (get ()) >>>) fs2
```

Figure 14: The mock-up combinator in parallel.

this gives us a communication scheme with messages going through the master node only if it is needed – similar to what is shown in the trace visualization in Fig. 15. One especially elegant aspect of this solution is that we can specify the type of *Future* to be used per backend with full interoperability between code using different backends, without even requiring to know about the actual type used for communication. We only specify that there has to be a compatible *Future* and do not care about any specifics. **OL: Fig. is not really clear. Do Figs with a lot of load? — fft?**

## 6 Skeletons

Now we have developed Parallel Arrows far enough to define some useful algorithmic skeletons that abstract typical parallel computations. While there are many possible skeletons to implement, we regard in detail here only some *map*-based and topological skeletons to demonstrate the power of PArrows.

### 6.1 map-based Skeletons

We start with *map*-based skeletons. The essential differences between the skeletons presented here are in terms of order of evaluation and work distribution but still provide the same output of a standard *map*.

**Parallel map and laziness.** The *parMap* skeleton (Figs. C 3, C 4) is probably the most common skeleton for parallel programs. We can implement it with *ArrowParallel* by



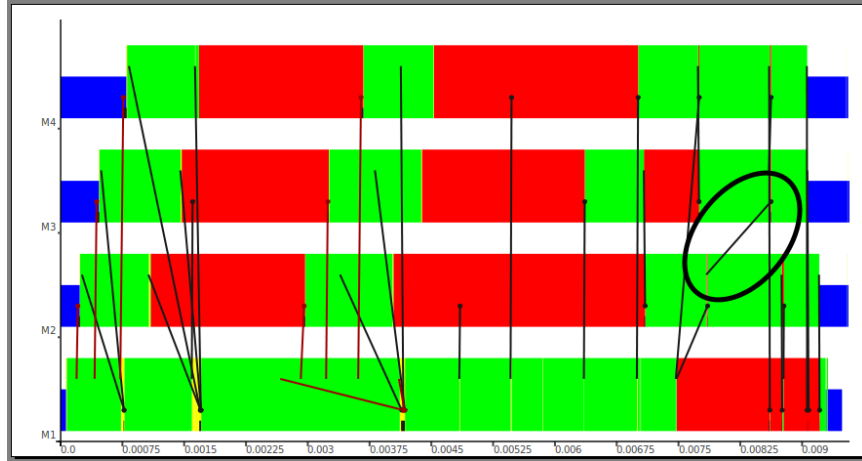


Figure 15: Communication between 4 Eden processes with Futures. Other than in Fig. 12, processes communicate directly (black lines between the bars, one example message is marked in the Figure) instead of always going through the master node (bottom bar).

repeating an arrow  $arr\ a\ b$  and then passing it into  $parEvalN$  to obtain an arrow  $arr\ [a]\ [b]$ . Just like  $parEvalN$ ,  $parMap$  is 100% strict. Because of this, it has the same restrictions as  $parEvalN$  as compared to  $parEvalNLazy$ . So it makes sense to also have a  $parMapStream$  (Figs. C 5, C 6) which behaves like  $parMap$ , but uses  $parEvalNLazy$  instead of  $parEvalN$ . The code of these two skeletons is quite straightforward, we show it in Appendix.

**Statically load-balancing parallel map.** Our  $parMap$  spawns every single computation in a new thread (at least for the instances of *ArrowParallel* we gave in this paper). This can be quite wasteful and a statically load-balancing *farm* (Figs. 16, 17) that equally distributes the workload over  $numCores$  workers seems useful. The definitions of the helper functions *unshuffle*, *takeEach*, *shuffle* (Fig. C 7) originate from an Eden skeleton<sup>7</sup>.

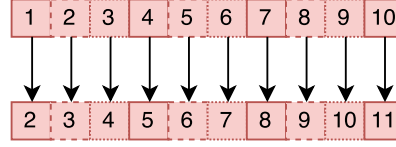
Since a *farm* is basically just  $parMap$  with a different work distribution, it is, again, 100% strict. So we can define *farmChunk* (Figs. 18, C 10) which uses  $parEvalNLazy$  instead of  $parEvalN$ . It is basically the same definition as for *farm*, with  $parEvalN$  replaced with  $parEvalNLazy$ .

## 6.2 Topological Skeletons

Even though many algorithms can be expressed by parallel maps, some problems require more sophisticated skeletons. The Eden library leverages this problem and already comes with more predefined skeletons<sup>8</sup>, among them a *pipe*, a *ring*, and a *torus* implementations

<sup>7</sup> Available on Hackage under <https://hackage.haskell.org/package/edenskel-2.1.0.0/docs/src/Control-Parallel-Eden-Map.html>.

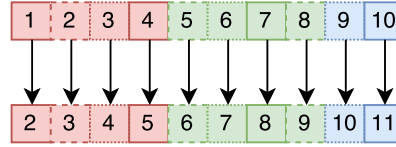
<sup>8</sup> Available on Hackage: <https://hackage.haskell.org/package/edenskel-2.1.0.0/docs/Control-Parallel-Eden-Topology.html>.

Figure 16: Schematic depiction of a *farm*, a statically load-balanced *parMap*.

```

farm :: (ArrowParallel arr a b conf,
        ArrowParallel arr [a] [b] conf, ArrowChoice arr) =>
        conf -> NumCores -> arr a b -> arr [a] [b]
farm conf numCores f =
  unshuffle numCores >>>
  parEvalN conf (repeat (mapArr f)) >>>
  shuffle

```

Figure 17: The definition of *farm*.Figure 18: Schematic depiction of *farmChunk*.

(Loogen *et al.*, 2003). These seem like reasonable candidates to be ported to our Arrow-based parallel Haskell. We aim to showcase that we can express more sophisticated skeletons with Parallel Arrows as well.

If we used the original definition of *parEvalN*, however, these skeletons would produce an infinite loop with the GpH and Par Monad backends which during runtime would result in the program crashing. This materializes with the usage of *loop* of the *ArrowLoop* type class and we think that this is due to difference of how evaluation is done in these backends when compared to Eden. An investigation of where this difference comes from is beyond the scope of this work, we only provide a workaround for these types of skeletons as such skeletons probably are not of much importance outside of a distributed memory environment. However our workaround enables users of the DSL to test their code within a shared memory setting even though other skeletons would be better suited to be run with them. The idea of the fix is to provide a *ArrowLoopParallel* typeclass that has two functions - *loopParEvalN* and *postLoopParEvalN* where the first is to be used inside an *loop* construct while the latter will be used right outside of the *loop*. This way we can delegate to the actual *parEvalN* in the spot where the backend supports it.

```

class ArrowParallel arr a b conf => ArrowLoopParallel arr a b conf where
  loopParEvalN :: conf -> [arr a b] -> arr [a] [b]
  postLoopParEvalN :: conf -> [arr a b] -> arr [a] [b]

```

As Eden has no problems with the looping skeletons, we use this instance:

**instance** (*ArrowChoice* *arr*, *ArrowParallel* *arr a b* *Conf*)  $\Rightarrow$  *ArrowLoopParallel* *arr a b* *Conf* **where**  
*loopParEvalN* = *parEvalN*  
*postLoopParEvalN* \_ = *evalN*

As the backends for the *Par* Monad and *GpH* have problems with *parEvalN* inside of *loop* their respective instances for *ArrowLoopParallel* look like this:

**instance** (*ArrowChoice* *arr*, *ArrowParallel* *arr a b* (*Conf* *b*))  $\Rightarrow$  *ArrowLoopParallel* *arr a b* (*Conf* *b*) **where**  
*loopParEvalN* \_ = *evalN*  
*postLoopParEvalN* = *parEvalN*

### 6.2.1 Parallel pipe

The parallel *pipe* skeleton is semantically equivalent to folding over a list  $[arr\ a\ a]$  of arrows with  $\gg\gg\gg$ , but does this in parallel, meaning that the arrows do not have to reside on the same thread/machine. We implement this skeleton using the *ArrowLoop* type class which gives us the  $loop :: arr\ (a, b)\ (c, b) \rightarrow arr\ a\ c$  combinator which allows us to express recursive fix-point computations in which output values are fed back as input. For example

$loop\ (arr\ (\lambda(a, b) \rightarrow (b, a : b)))$

which is the same as

$loop\ (arr\ snd\ \&\&\&\ arr\ (uncurry\ ()))$

defines an arrow that takes its input *a* and converts it into an infinite stream  $[a]$  of it. Using this to our advantage gives us a first draft of a pipe implementation (Fig. 19) by plugging in the parallel evaluation call *evalN conf fs* inside the second argument of  $\&\&\&$  and then only picking the first element of the resulting list with *arr last*.

Sometimes, this *pipe* definition can be a bit inconvenient, especially if we want to pipe arrows of mixed types together, i.e. *arr a b* and *arr b c*. By wrapping these two arrows inside a bigger arrow  $arr\ (([a], [b]), [c])\ (([a], [b]), [c])$  suitable for *pipe*, we can define *pipe2* as in Fig. 21.

Note that extensive use of *pipe2* over *pipe* with a hand-written combination data type will probably result in worse performance because of more communication overhead from the many calls to *parEvalN* inside of *evalN*. Nonetheless, we can define a version of parallel piping operator  $| \gg\gg\gg |$ , which is semantically equivalent to  $\gg\gg\gg$  similarly to other parallel syntactic sugar from Appendix D.

### 6.2.2 Ring skeleton

Eden comes with a ring skeleton<sup>9</sup> (Fig. 22) implementation that allows the computation of a function  $[i] \rightarrow [o]$  with a ring of nodes that communicate with each other. Its input is a node function  $i \rightarrow r \rightarrow (o, r)$  in which *r* serves as the intermediary output that gets sent to

<sup>9</sup> Available on Hackage: <https://hackage.haskell.org/package/edenskel-2.1.0.0/docs/Control-Parallel-Eden-Topology.html>

```

pipeSimple :: (ArrowLoop arr, ArrowLoopParallel arr a a conf) =>
  conf -> [arr a a] -> arr a a
pipeSimple conf fs =
  loop (arr snd &&&
    (arr (uncurry (:)) >>> lazy) >>> loopParEvalN conf fs)) >>>
  arr last

```

Figure 19: A first implementation of the *pipe* skeleton expressed with Parallel Arrows. Note that the use of *lazy* (Fig. C 8) is essential as without it programs using this definition would never halt. We need to enforce that the evaluation of the input  $[a]$  terminates before passing it into *evalN*.

However, using this definition directly will make the master node a potential bottleneck in distributed environments as described in Section ???. Therefore, we introduce a more sophisticated version that internally uses Futures and obtain the final definition of *pipe* in Fig. 20.

```

pipe :: (ArrowLoop arr, ArrowLoopParallel arr (fut a) (fut a) conf,
  Future fut a conf) =>
  conf -> [arr a a] -> arr a a
pipe conf fs = unliftFut conf (pipeSimple conf (map (liftFut conf) fs))
liftFut :: (Arrow arr, Future fut a conf, Future fut b conf) =>
  conf -> arr a b -> arr (fut a) (fut b)
liftFut conf f = get conf >>> f >>> put conf
unliftFut :: (Arrow arr, Future fut a conf, Future fut b conf) =>
  conf -> arr (fut a) (fut b) -> arr a b
unliftFut conf f = put conf >>> f >>> get conf

```

Figure 20: Final definition of the *pipe* skeleton with Futures.

the neighbour of each node. This data is sent over direct communication channels, the so called ‘remote data’. We depict it in Appendix, Fig. C 11.

We can rewrite this functionality easily with the use of *loop* as the definition of the node function,  $\text{arr } (i, r) (o, r)$ , after being transformed into an arrow, already fits quite neatly into the *loop*’s  $\text{arr } (a, b) (c, b) \rightarrow \text{arr } a c$ . In each iteration we start by rotating the intermediary input from the nodes  $[fut r]$  with *second* (*rightRotate* >>> *lazy*) (Fig. C 8). Similarly to the *pipe* from Section 6.2.1 (Fig. 19), we have to feed the intermediary input into our *lazy* (Fig. C 8) arrow here, or the evaluation would fail to terminate. The reasoning is explained by Loogen (2012) as a demand problem.

Next, we zip the resulting  $[(i), [fut r]]$  to  $[(i, fut r)]$  with *arr* (*uncurry zip*) so we can feed that into our input arrow  $\text{arr } (i, r) (o, r)$ , which we transform into  $\text{arr } (i, fut r) (o, fut r)$  with *second get* >>> *f* >>> *second put* before converting it into a parallel arrow  $\text{arr } [(i, fut r)] [(o, fut r)]$  with the help of *repeat* and *loopParEvalN* to get an output list  $[(o, fut r)]$ . Finally we unzip this list into  $[(o), [fut r]]$ . Plugging this arrow  $\text{arr } [(i), [fut r]] [(o), fut r]$  into the definition of *loop* from earlier gives us  $\text{arr } [i] [o]$ , our ring arrow (Fig. 23). To make sure this algorithm has speedup on shared-memory machines as well, we pass the result of this arrow to *postLoopParEvalN conf* (*repeat* (*arr id*)). This combinator can, for example, be used to calculate the shortest paths in a graph using Warshall’s algorithm.

```

pipe2 :: (ArrowLoop arr, ArrowChoice arr,
         ArrowLoopParallel arr (fut (([a],[b]),[c])) (fut (([a],[b]),[c])) conf,
         Future fut (([a],[b]),[c]) conf) =>
  conf -> arr a b -> arr b c -> arr a c
pipe2 conf f g =
  (arr return &&& arr (const [])) &&& arr (const []) >>>
  pipe conf (replicate 2 (unify f g)) >>>
  arr snd >>>
  arr head
where
  unify :: (ArrowChoice arr) =>
    arr a b -> arr b c -> arr (([a],[b]),[c]) (([a],[b]),[c])
  unify f' g' =
    (mapArr f' *** mapArr g') *** arr (const []) >>>
    arr (\((b,c),a) -> ((a,b),c))
(| >>> |) :: (ArrowLoop arr, ArrowChoice arr,
             ArrowLoopParallel arr (fut (([a],[b]),[c])) (fut (([a],[b]),[c])) (),
             Future fut (([a],[b]),[c]) ()) =>
  arr a b -> arr b c -> arr a c
(| >>> |) = pipe2 ()

```

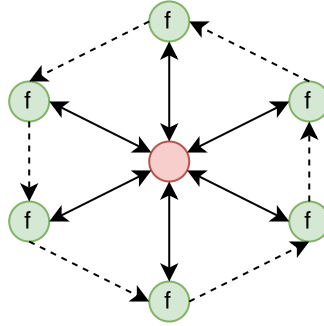
Figure 21: Definition of *pipe2* and  $(| \gg \gg |)$ , a parallel  $\gg$ .

Figure 22: Schematic depiction of the ring skeleton.

### 6.2.3 Torus skeleton

If we take the concept of a *ring* from Section 6.2.2 one dimension further, we obtain a *torus* skeleton (Fig. 24, 25). Every node sends and receives data from horizontal and vertical neighbours in each communication round. With our Parallel Arrows we re-implement the *torus* combinator<sup>10</sup> from Eden—yet again with the help of the *ArrowLoop* type class.

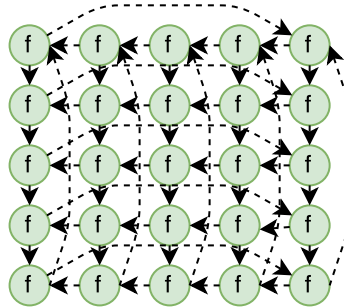
Similar to the *ring*, we start by rotating the input (Fig. C 8), but this time not only in one direction, but in two. This means that the intermediary input from the neighbour nodes has to be stored in a tuple  $(([fut\ a], [fut\ b]))$  in the second argument (loop only allows for two

<sup>10</sup> Available on Hackage: <https://hackage.haskell.org/package/edenskel-2.1.0.0/docs/Control-Parallel-Eden-Topology.html>.

```

ring :: (Future fut r conf,
        ArrowLoop arr,
        ArrowLoopParallel arr (i,fut r) (o,fut r) conf,
        ArrowLoopParallel arr o o conf) =>
  conf -> arr (i,r) (o,r) -> arr [i] [o]
ring conf f =
  loop (second (rightRotate >>> lazy) >>>
        arr (uncurry zip) >>>
        loopParEvalN conf (repeat (second (get conf) >>> f >>> second (put conf))) >>>
        arr unzip) >>>
  postLoopParEvalN conf (repeat (arr id))

```

Figure 23: Definition of the *ring* skeleton.Figure 24: Schematic depiction of the *torus* skeleton.

arguments) of our looped arrow  $arr ([c], ([fut a], [fut b])) ([d], ([fut a], [fut b]))$  and our rotation arrow becomes

$$second ((mapArr rightRotate >>> lazy) *** (arr rightRotate >>> lazy))$$

instead of the singular rotation in the ring as we rotate  $[fut a]$  horizontally and  $[fut b]$  vertically. Then, we zip the inputs for the input arrow with

$$arr (uncurry3 zipWith3 lazyzip3)$$

from  $([c], ([fut a], [fut b]))$  to  $[(c, fut a, fut b)]$ , which we then evaluate in parallel.

This, however, is more complicated than in the ring case as we have one more dimension of inputs that needs to be transformed. We first have to *shuffle* all the inputs to then pass them into  $loopParEvalN conf (repeat (ptorus conf f))$  to get an output of  $[(d, fut a, fut b)]$ . We then unshuffle this list back to its original ordering by feeding it into  $arr (uncurry unshuffle)$  which takes the input length we saved one step earlier as additional input to get a result matrix  $[[[(d, fut a, fut b)]]]$ . Finally, we unpack this matrix with  $arr (map unzip3) >>> arr unzip3 >>> threetotwo$  to get  $([d], ([fut a], [fut b]))$ .

This internal looping computation is once again fed into *loop* and we also compose a final  $postLoopParEvalN conf (repeat (arr id))$  for the same reasons as explained for the *ring* skeleton.

```

torus :: (Future fut a conf, Future fut b conf,
         ArrowLoop arr, ArrowChoice arr,
         ArrowLoopParallel arr (c, fut a, fut b) (d, fut a, fut b) conf,
         ArrowLoopParallel arr [d] [d] conf) =>
  conf -> arr (c, a, b) (d, a, b) -> arr [[c]] [[d]]
torus conf f =
  loop (second ((mapArr rightRotate >>> lazy) *** (arr rightRotate >>> lazy)) >>>
        arr (uncurry3 (zipWith3 lazyzip3)) >>>
        arr length &&& (shuffle >>> loopParEvalN conf (repeat (ptorus conf f))) >>>
        arr (uncurry unshuffle) >>>
        arr (map unzip3) >>> arr unzip3 >>> threetotwo) >>>
  postLoopParEvalN conf (repeat (arr id))
ptorus :: (Arrow arr, Future fut a conf, Future fut b conf) =>
  conf ->
  arr (c, a, b) (d, a, b) ->
  arr (c, fut a, fut b) (d, fut a, fut b)
ptorus conf f =
  arr (λ~(c, a, b) -> (c, get conf a, get conf b)) >>>
  f >>>
  arr (λ~(d, a, b) -> (d, put conf a, put conf b))

```

Figure 25: Definition of the *torus* skeleton. The definitions of *lazyzip3*, *uncurry3* and *threetotwo* have been omitted and can be found in Fig. C 9

As an example of using this skeleton, Loogen *et al.* (2003) showed the matrix multiplication using the Gentleman algorithm (1978). An adapted version can be found in Fig. 26. If we compare the trace from a call using our arrow definition of the *torus* (Fig. 27) with the Eden version (Fig. 28) we can see that the behaviour of the arrow version and execution times are comparable. We discuss further benchmarks on larger clusters and in a more detail in the next section.

## 7 Performance results and discussion

In the following section, we describe the benchmarks of our parallel DSL and algorithmic skeletons conducted. We start by explaining the hardware and software stack and also elaborate on which benchmarks programs were used and also which parallel Haskell were used in which setting and why. Before we go into detail on the benchmarks we also address the issue of poor performance gains when using hyper-threading and our reasoning behind not including hyper-threaded cores in our benchmarks. Finally, we show that PArrows hold up in terms of performance when compared to the original parallel Haskell used as backends in this paper, starting with the shared-memory variants (GpH, *Par* Monad and Eden CP) and concluding with Eden as a distributed backend.

```

type Matrix = [[Int]]

prMM_torus :: Int → Int → Matrix → Matrix → Matrix
prMM_torus numCores problemSizeVal m1 m2 =
  combine $ torus () (mult torusSize) $ zipWith (zipWith (,)) (split m1) (split m2)
  where torusSize = (floor ∘ sqrt) $ fromIntegral numCores
        combine = concat ∘ (map (foldr (zipWith (++) (repeat [])))
        split = splitMatrix (problemSizeVal `div` torusSize)

-- Function performed by each worker
mult :: Int → ((Matrix, Matrix), [Matrix], [Matrix]) → (Matrix, [Matrix], [Matrix])
mult size ((sm1, sm2), sm1s, sm2s) = (result, toRight, toBottom)
  where toRight = take (size - 1) (sm1 : sm1s)
        toBottom = take (size - 1) (sm2' : sm2s)
        sm2' = transpose sm2
        sms = zipWith prMMTr (sm1 : sm1s) (sm2' : sm2s)
        result = foldl1' matAdd sms

```

Figure 26: Adapted matrix multiplication in Eden using a the *torus* skeleton. *prMM\_torus* is the parallel matrix multiplication. *mult* is the function performed by each worker. *prMMTr* calculates  $AB^T$  and is used for the (sequential) calculation in the chunks. *splitMatrix* splits the Matrix into chunks. *matAdd* calculates  $A + B$ . Omitted definitions can be found in C 13.

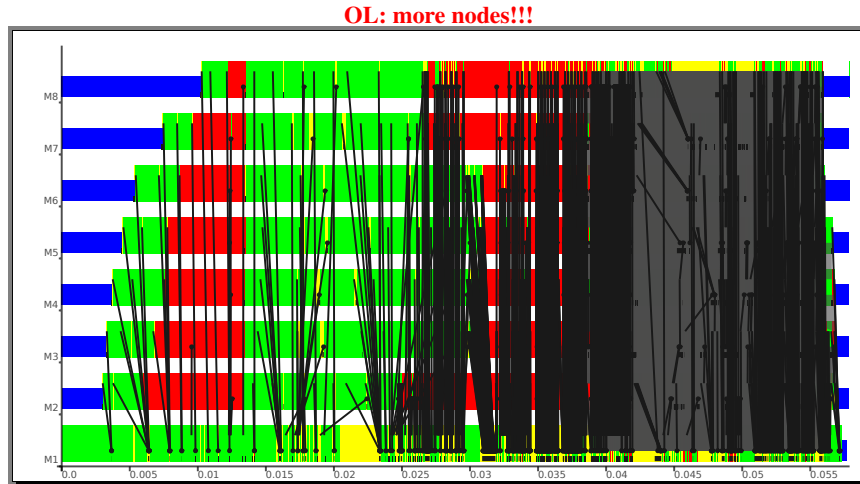


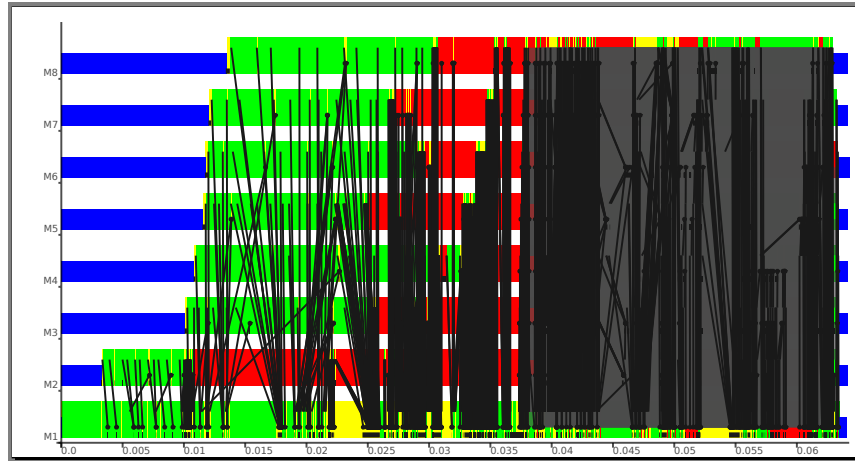
Figure 27: Matrix Multiplication with *torus* (PArrows).

## 7.1 Preliminaries

### 7.1.1 Hardware and Software used

Benchmarks were run both in a shared and in a distributed memory setting. All benchmarks were done on the Glasgow GPG Beowulf cluster, consisting of 16 machines with 2 Intel® Xeon® E5-2640 v2 and 64 GB of DDR3 RAM each. Each processor has 8 cores and 16 (hyper-threaded) threads with a base frequency of 2 GHz and a turbo frequency of 2.50 GHz. This results in a total of 256 cores and 512 threads for the whole cluster. The



Figure 28: Matrix Multiplication with *torus* (Eden).

operating system was Ubuntu 14.04 LTS with Kernel 3.19.0-33. Non-surprisingly, we found that hyper-threaded 32 cores do not behave in the same manner as real 16 cores (numbers here for a single machine). We disregarded the hyper-threading ability in most of the cases.

Apart from Eden, all benchmarks and libraries were compiled with Stack’s<sup>11</sup> lts-7.1 GHC compiler which is equivalent to a standard GHC 8.0.1 with the base package in version 4.9.0.0. Stack itself was used in version 1.3.2. For GpH in its Multicore variant we used the parallel package in version 3.2.1.0<sup>12</sup>, while for the *Par* monad we used monad-par in version 0.3.4.8<sup>13</sup>. For all Eden tests, we used its GHC-Eden compiler in version 7.8.2<sup>14</sup> together with OpenMPI 1.6.5<sup>15</sup>.

Furthermore, all benchmarks were done with help of the bench<sup>16</sup> tool in version 1.0.2 which uses criterion ( $\geq 1.1.1.0$  &&  $< 1.2$ )<sup>17</sup> internally. All runtime data (mean runtime, max stddev, etc.) was collected with this tool if not mentioned otherwise.

We used a single node with 16 real cores as a shared memory testbed and the whole grid with 256 real cores as a device to test our distributed memory software.

### 7.1.2 Benchmarks

We used multiple tests that originated from different sources. Most of them are parallel mathematical computations, initially implemented in Eden. Table 1 summarises.

<sup>11</sup> see <https://www.haskellstack.org/>

<sup>12</sup> see <https://hackage.haskell.org/package/parallel-3.2.1.0>

<sup>13</sup> see <https://hackage.haskell.org/package/monad-par-0.3.4.8>

<sup>14</sup> see [http://www.mathematik.uni-marburg.de/~eden/?content=build\\_edен\\_7\\_&navi=build](http://www.mathematik.uni-marburg.de/~eden/?content=build_edен_7_&navi=build)

<sup>15</sup> see <https://www.open-mpi.org/software/ompi/v1.6/>

<sup>16</sup> see <https://hackage.haskell.org/package/bench>

<sup>17</sup> see <https://hackage.haskell.org/package/criterion-1.1.1.0>

<sup>18</sup> actual code from: <http://community.haskell.org/~simonmar/par-tutorial.pdf> and <https://github.com/simonmar/parconc-examples>

Table 1: The benchmarks we use in this paper.

Name	Area	Type	Origin	Source
Rabin–Miller test	Mathematics	<i>parMap + reduce</i>	Eden	Lobachev (2012)
Jacobi sum test	Mathematics	<i>workpool + reduce</i>	Eden	Lobachev (2012)
Gentleman	Mathematics	<i>torus</i>	Eden	Loogen <i>et al.</i> (2003)
Sudoku	Puzzle	<i>parMap</i>	<i>Par Monad</i>	Marlow <i>et al.</i> (2011) <sup>18</sup>

Rabin–Miller test is a probabilistic primality test that iterates multiple (here: 32–256) ‘subtests’. Should a subtest fail, the input is definitely not a prime. If all  $n$  subtest pass, the input is composite with the probability of  $1/4^n$ .

Jacobi sum test or APRCL is also a primality test, that however, guarantees the correctness of the result. It is probabilistic in the sense that its run time is not certain. Unlike Rabin–Miller test, the subtests of Jacobi sum test have very different durations. Lobachev (2011) discusses some optimisations of parallel APRCL. Generic parallel implementations of Rabin–Miller test and APRCL were presented in Lobachev (2012).

‘Gentleman’ is a standard Eden test program, developed for their *torus* skeleton. It implements a Gentleman’s algorithm for parallel matrix multiplication (Gentleman, 1978). We ported an Eden based version (Loogen *et al.*, 2003) to PArrows.

A parallel Sudoku solver was used by Marlow *et al.* (2011) to compare *Par Monad* to GpH, and we ported it to PArrows.

### 7.1.3 What parallel Haskells run where

The *Par monad* and GpH – in its multicore version (Marlow *et al.*, 2009) – can be executed on shared memory machines only. Although GpH is available on distributed memory clusters, and newer distributed memory Haskells such as HdP exist, current support of distributed memory in PArrows is limited to Eden. We used the MPI backend of Eden in a distributed memory setting. However, for shared memory Eden features a “CP” backend that merely copies the memory blocks between distributed heaps. In this mode, Eden still operates in the “nothing shared” setting, but is adapted better to multicore machines. We label this version of Eden in the plots as “Eden CP”.

### 7.1.4 Effect of hyper-threading

In preliminary tests, the PArrows version of Rabin–Miller test on a single node of the Glasgow cluster showed almost linear speedup on up to 16 shared-memory cores (Fig. ??). The speedup of 64-task PArrows/Eden at 16 real cores version was 13.65 giving a parallel efficiency of 85.3%. However, if we increased the number of requested cores to 32 – i.e. if we use hyper-threading on 16 real cores – the speedup did not increase that well. It was merely 15.99 for 32 tasks with PArrows/Eden. This was worse for other backends. As for 64 tasks, we obtained a speedup of 16.12 with PArrows/Eden at 32 hyper-threaded cores and only 13.55 with PArrows/GpH. The parallel efficiencies were 50.4% and 42.3%, respectively. The Eden version used here was Eden CP, the ‘share nothing’ SMP build.

In the distributed memory setting the same effect ensues. We obtain plummeting speedup of 124.31 at 512 hyper-threaded cores, whereas it was 213.172 for 256 real cores. Apparently, hyper-threading in the Glasgow cluster fails to execute two parallel Haskell processes with full-fledged parallelism.

**MB: fix this when benchmarks are redone** With this in mind, the performance measurements in the Section 7.2 use only real cores as the purpose of this paper is to show the performance of PArrows and not to investigate parallel performance with hyper-threading in more detail.

## 7.2 Benchmark results

In the following paragraphs we will go into detail on how well PArrows perform when compared to versions of the benchmark programs implemented with the original parallel Haskells that were used in the backends. We start by comparing Speedups and Overheads of for the shared memory backends and conclude with OpenMPI variants of the Eden-enabled backend as a representative of a distributed memory backend.

### 7.2.1 Shared memory

**Speedup** The Rabin–Miller test benchmark showed almost linear speedup for both 32 and 64 tasks, the performance is slightly better in the latter case: 13.7 at 16 cores for input  $2^{11213} - 1$  and 64 tasks in the best case scenario with Eden CP. The performance of the Sudoku benchmark merely reaches a speedup of 9.19 (GpH), 8.78 (Par Monad), 8.14 (Eden CP) for 16 cores and 1000 Sudokus. In contrast to Rabin–Miller, here the *GpH* Monad backend seems to be the best of all, while Rabin–Miller profited most from Eden CP (i.e., Eden with direct memory copy) implementation of PArrows. Gentleman on shared memory has a plummeting speedup curve with GpH and *Par* Monad and logarithmically increasing speedup for Eden-based version. The latter reached a speedup of 6.56 at 16 cores.

**MB: Ich hab ein bisschen mehr Daten hinzugefügt für Sudoku**

**Overhead** We compared the overhead of our PArrows implementations to the original parallel Haskells. We basically implemented the test programs both in PArrows and in traditional style, benchmarked both and compare the mean overhead, i.e. the *relative* difference between both benchmarks with same settings. The error margin of the benchmarks, supplied by criterion package, goes into the mean overhead computation.

For the shared memory Rabin–Miller test benchmark, implemented with PArrows both with Eden CP and with *Par* Monad backends, **MB: stimmt das so noch? Ich bin die Daten da nicht zu 100% durch gegangen, aber die Aussage always finde ich etwas viel, almost always?** the zero **MB: almost** always lay in the error margin of the mean overhead. This means that though we have measured some difference (against or even in favour of PArrows), it could be merely the error margin of the benchmarks and the difference might not be existent. In the following, we call the contrary case “significant”. In other words, we notice no significant slow-down through PArrows here. For GpH backend there was only a small significant overhead of 8% at 16 cores with 32 tasks and input value  $2^{11213} - 1$ . For Sudoku the situation is slightly different. There is a minimal (1.4%)

significant speed improvement with PArrows Eden CP version when compared with the base Eden CP benchmark. However, with increasing number of cores the error margin reaches zero again. The *Par* Monad shows a similar development. The GpH version shows a small significant speed *improvement* from PArrows of 4.2%. The Gentleman multiplication with Eden CP shows a minor significant overhead of 2.6% at 8 cores and an insignificant improvement at 16 cores.

We observe a low (if significant at all) overhead, induced by PArrows in the shared memory setting.

### 7.2.2 Distributed Memory

**Speedup** The speedup of distributed memory Rabin–Miller benchmark with PArrows and distributed Eden backend showed an almost linear speedup sans some issues in the middle because of unfortunate task distribution. As seen in Fig. 29, we reached a speedup of 213.4 with PArrows at 256 cores (vs. 207.7 with pure Eden). We managed to measure the speedup of Jacobi sum test for sufficient large inputs only in a massively distributed setting, because of memory limitations. We improved there from 9193 seconds (128 cores) to 1649 seconds (256 cores) in our PArrows version, so we only include a graph for a run  $2^{3217} - 1$  in the supplementary material. This speedup at about 11 for both PArrows and Eden for more than 64 cores. There is apparently not enough work for that many cores. The Gentleman test with input 4096 had an almost linear speedup first, then plummeted between 128 and 224 cores, and recovered at 256 cores with speedup of 129.

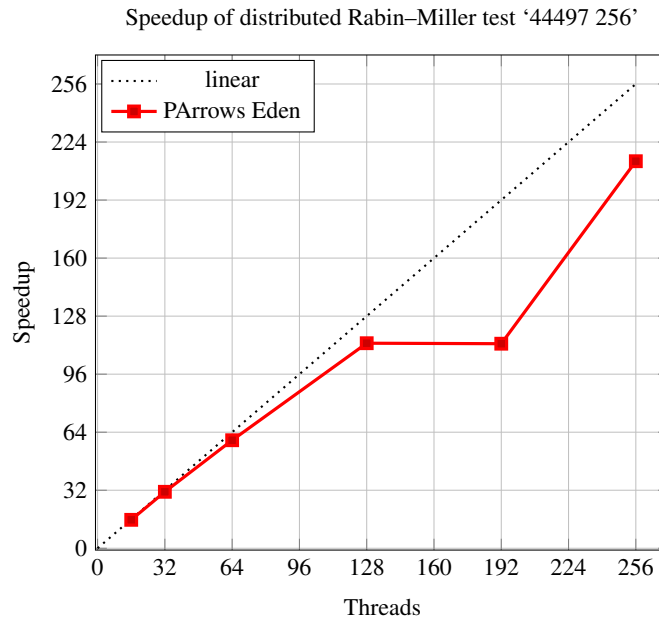


Figure 29: Speedup of the distributed Rabin–Miller test benchmark with the Eden backend

Table 2: Overhead in the shared memory benchmarks

Benchmark	vs.	mean of mean overheads	maximum normalized stdDev	runtime for 16 cores
Sudoku 1000	Eden CP	<b>-0.02147</b>	0.05057	1.17016
	GpH	<b>-0.00823</b>	0.00705	1.11486
	Par Monad	<b>-0.01252</b>	0.02148	1.13852
Gentleman 512	Eden CP	0.00814	0.06777	1.6574
Rabin–Miller test 11213 32	Eden CP	0.00791	0.05156	5.16205
	GpH	0.03487	0.06904	5.28257
	Par Monad	<b>-0.02472</b>	0.18622	5.84164
Rabin–Miller test 11213 64	Eden CP	0.00211	0.01924	10.31537
	GpH	0.01561	0.01282	10.56292
	Par Monad	<b>-0.03958</b>	0.16513	11.37999

**Overhead** We use our above mean overhead quality measure and the notion of significance also for distributed memory benchmarks. The mean overhead of Rabin–Miller test in the distributed memory setting ranges from 0.29% to  $-2.8\%$  (last value in favor of PArrows), but these values are not significant. A sole significant (by a very low margin) overhead is 0.35% at 64 cores. We measured the mean overhead for Jacobi benchmark for an input of  $2^{3217} - 1$  for up to 256 cores. We reached a maximum overhead of 0.32% at 256 cores. In all cases it was not significant, the zero was inside the error margin. Mean overhead for distributed Gentleman multiplication was also low. Significant values include 1.23% at 64 cores, 6.4% at 128 cores, and 2.4% at 256 cores. It took PArrows 64.2 seconds at 256 cores to complete the benchmark.

Similar to the shared memory setting, PArrows only imply a very low penalty with distributed memory that is outweighed by their convenience and usefulness to the user.

### 7.3 Discussion

**MB: Schau hier vll nochmal drüber, das ist etwas unsauber formuliert evtl.?** Summing up, PArrows performed with little to no overhead. Tables 2 and 3 clarify this once more: The PArrow enabled versions trade blows with the vanilla counterparts when comparing the mean of the mean overheads. If we combine these findings with the convenience of our DSL, PArrows seem like a great improvement over the respective backends with.

Table 3: Overhead in the distributed memory benchmarks

Benchmark	vs.	mean of mean overheads	maximum normalized stdDev	runtime for 256 cores
Gentleman 4096	Eden	0.00671	0.01456	110.05212
Rabin–Miller test 44497 256	Eden	<b>-0.00505</b>	0.02929	164.88379
Jacobi sum test 3217	Eden	<b>-0.00738</b>	0.01595	634.64167

## 8 Conclusion

Arrows are a generic concept that allows for powerful composition combinators. To our knowledge we are first to represent *parallel* computation with Arrows. Arrows turn out to be a useful tool for composing parallel programs. We have shown, that, in order to have a generic and extensible parallel Haskell, we do not have to restrict ourselves to a monadic interface. Instead, we use Arrows which are a more general concept than Monads, but still allow for powerful composition. Furthermore, we think Arrows are a better fit to parallelize pure code than a monadic solution as regular functions are already Arrows and can be used with our DSL in a more natural way. We manage to retain this nice property of parallel Haskell-like Eden or GpH (which use pure constructs) while still having a generic and composable interface. The DSL natively allows for parallelization of monadic code via the Kleisli type and additionally allows to parallelize any Arrow type that has an instance for *ArrowChoice* (note that some skeletons require an additional *ArrowLoop* instance). Parallel Arrows, as presented here, feature an implementation of the *ArrowParallel* type class for GpH Haskell, *Par* Monad, and Eden. With our approach parallel programs can be ported across these flavours with little to no effort. It is quite straightforward to add further backends. Performance-wise, Parallel Arrows are on par with existing parallel Haskell-like, as they only introduce minor overhead in some of our benchmarks. The benefit is, however, the greatly increased portability of parallel programs.

### 8.1 Future Work

Our PArrows DSL can be expanded to further parallel Haskell-like. More specifically we target HdpH (Maier *et al.*, 2014) for this future extension. HdpH is a modern distributed Haskell that would benefit from our Arrow notation. Further Future-aware versions of Arrow combinators can be defined. Existing combinators could also be improved. Arrow-based notation might enable further compiler optimizations.

More experiences with seamless porting of parallel PArrows-based programs across the backends are welcome. Of course, we are ourselves working on expanding both our skeleton library and the number of skeleton-based parallel programs that use our DSL to be portable across flavours of parallel Haskell. It would also be interesting to see a hybrid of PArrows and Accelerate (McDonnell *et al.*, 2015). Ports of our approach to other languages like Frege, Eta or Java directly are in an early development stage.

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## A Utility Arrows

Following are definitions of some utility Arrows used in this paper that have been left out for brevity. We start with the *second* combinator from Hughes (2000), which is a mirrored version of *first*, which is for example used in the definition of *\*\*\**:

$$\begin{aligned} \text{second} &:: \text{Arrow } arr \Rightarrow arr\ a\ b \rightarrow arr\ (c, a)\ (c, b) \\ \text{second } f &= arr\ swap >>> \text{first } f >>> arr\ swap \\ \text{where } swap\ (x, y) &= (y, x) \end{aligned}$$

Next, we give the definition of *evalN* which also helps us to define *map*, and *zipWith* on Arrows. The *evalN* combinator in Fig. A 1 converts a list of arrows  $[arr\ a\ b]$  into an arrow  $arr\ [a]\ [b]$ .

The *mapArr* combinator (Fig. A 2) lifts any arrow  $arr\ a\ b$  to an arrow  $arr\ [a]\ [b]$ . The original inspiration was from (Hughes, 2005b), but the definition as then unified with *evalN*.

Finally, with the help of *mapArr* (Fig. A 2), we can define *zipWithArr* (Fig. A 3) that lifts any arrow  $arr\ (a, b)\ c$  to an arrow  $arr\ ([a], [b])\ [c]$ .

These combinators make use of the *ArrowChoice* type class which provides the  $\parallel$  combinator. It takes two Arrows  $arr\ a\ c$  and  $arr\ b\ c$  and combines them into a new Arrow

```

evalN :: (ArrowChoice arr) => [arr a b] -> arr [a] [b]
evalN (f : fs) = arr listcase >>>>
  arr (const []) ||| (f *** evalN fs >>>> arr (uncurry ()))
  where listcase [] = Left ()
        listcase (x : xs) = Right (x, xs)
evalN [] = arr (const [])

```

Figure A 1: The definition of *evalN*

```

mapArr :: ArrowChoice arr => arr a b -> arr [a] [b]
mapArr = evalN o repeat

```

Figure A 2: The definition of *map* over Arrows.

*arr (Either a b) c* which pipes all *Left a*'s to the first arrow and all *Right b*'s to the second arrow:

```

(|||) :: ArrowChoice arr a c -> arr b c -> arr (Either a b) c

```

## B Profunctor Arrows

In Fig. B 1 we show how specific Profunctors can be turned into Arrows. This works because Arrows are strong Monads in the bicategory Prof of Profunctors as shown by Asada (2010). Note that in Standard GHC (*>>>>*) has the type (*>>>>*) :: *Category cat* => *cat a b* -> *cat b c* -> *cat a c* and is therefore not part of the *Arrow* typeclass like presented in this paper.

## C Omitted Function Definitions

We have omitted some function definitions in the main text for brevity, and redeem this here.

We begin with warping Eden's build-in *RemoteData* to *Future* in Figure C 1

Next, we have the definition of *BasicFuture* in Fig. C 2 and the corresponding *Future* instances.

Figures C 3–C 6 show the definitions and a visualizations of two parallel *map* variants, defined using *parEvalN* and its lazy counterpart.

Arrow versions of Eden's *shuffle*, *unshuffle* and the definition of *takeEach* are in Figure C 7. Similarly, Figure C 8 contains the definition of arrow versions of Eden's *lazy* and *rightRotate* utility functions. Fig. C 9 contains Eden's definition of *lazyzip3* together with the utility functions *uncurry3* and *threetotwo*. The full definition of *farmChunk* is in Figure C 10. Eden definition of *ring* skeleton is in Figure C 11. It follows Loogen (2012).

<sup>19</sup> for additional information on the typeclasses used, see: <https://hackage.haskell.org/package/profunctors-5.2.1/docs/Data-Profunctor.html> and <https://hackage.haskell.org/package/base-4.9.1.0/docs/Control-Category.html>

```
zipWithArr :: ArrowChoice arr => arr (a,b) c -> arr ([a],[b]) [c]
zipWithArr f = (arr $ \ (as,bs) -> zipWith (,) as bs) >>> mapArr f
```

Figure A 3: *zipWith* over arrows.

```
instance (Category p, Strong p) => Arrow p where
  arr f = dimap id f id
  first = first'

instance (Category p, Strong p, Costrong p) => ArrowLoop p where
  loop = loop'

instance (Category p, Strong p, Choice p) => ArrowChoice p where
  left = left'
```

Figure B 1: Profunctors as Arrows<sup>19</sup>

The *parEval2* skeleton is defined in Figure C 12. We start by transforming the  $(a, c)$  input into a two-element list  $[Either\ a\ c]$  by first tagging the two inputs with *Left* and *Right* and wrapping the right element in a singleton list with *return* so that we can combine them with *arr (uncurry (:))*. Next, we feed this list into a parallel arrow running on two instances of  $f\ +\ +\ +\ g$  as described in the paper. After the calculation is finished, we convert the resulting  $[Either\ b\ d]$  into  $([b],[d])$  with *arr partitionEithers*. The two lists in this tuple contain only one element each by construction, so we can finally just convert the tuple to  $(b, d)$  in the last step. Furthermore, Fig. C 13 contains the omitted definitions of *prMMTr* (which calculates  $AB^T$  for two matrices  $A$  and  $B$ ), *splitMatrix* (which splits the a matrix into chunks), and lastly *matAdd*, that calculates  $A + B$  for two matrices  $A$  and  $B$ .

## D Syntactic Sugar

Finally, we also give the definitions for some syntactic sugar for PArrows, namely *\*\*\** and *&&&*. For basic arrows, we have the *\*\*\** combinator (Fig. 3) which allows us to combine two arrows *arr a b* and *arr c d* into an arrow *arr (a, c) (b, d)* which does both computations at once. This can easily be translated into a parallel version *\*\*\** with the use of *parEval2*, but for this we require a backend which has an implementation that does not require any configuration (hence the  $()$  as the *conf* parameter):

```
(|***|) :: (ArrowChoice arr, ArrowParallel arr (Either a c) (Either b d) ()) =>
  arr a b -> arr c d -> arr (a, c) (b, d)
(|***|) = parEval2 ()
```

We define the parallel *&&&* in a similar manner to its sequential pendant *&&&* (Fig. 3):

```
(|&&&|) :: (ArrowChoice arr, ArrowParallel arr (Either a a) (Either b c) ()) =>
  arr a b -> arr a c -> arr a (b, c)
(|&&&|) f g = (arr $ \ a -> (a, a)) >>> f |***| g
```

```

data RemoteData a = RD { rd :: RD a }
put' :: (Arrow arr) ⇒ arr a (BasicFuture a)
put' = arr BF
get' :: (Arrow arr) ⇒ arr (BasicFuture a) a
get' = arr (λ(∼(BF a)) → a)
instance NFData (RemoteData a) where
  rnf = rnf ∘ rd
instance Trans (RemoteData a)
instance (Trans a) ⇒ Future RemoteData a Conf where
  put _ = put'
  get _ = get'
instance (Trans a) ⇒ Future RemoteData a () where
  put _ = put'
  get _ = get'

```

Figure C 1: *RD*-based *RemoteData* version of *Future* for the Eden backend.

```

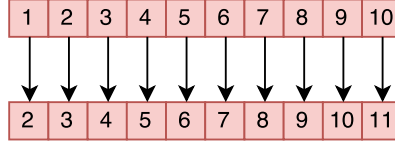
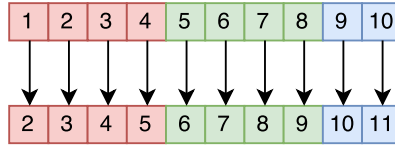
data BasicFuture a = BF a
put' :: (Arrow arr) ⇒ arr a (BasicFuture a)
put' = arr BF
get' :: (Arrow arr) ⇒ arr (BasicFuture a) a
get' = arr (λ(∼(BF a)) → a)
instance NFData a ⇒ NFData (BasicFuture a) where
  rnf (BF a) = rnf a
instance Future BasicFuture a (Conf a) where
  put _ = put'
  get _ = get'
instance Future BasicFuture a () where
  put _ = put'
  get _ = get'

```

Figure C 2: The *BasicFuture* type and its *Future* instance for the *Par* Monad and GpH Haskell backends.

## Arrows for Parallel Computations

39

Figure C 3: Schematic depiction of *parMap*.
$$\begin{aligned} \text{parMap} &:: (\text{ArrowParallel } \text{arr } a \ b \ \text{conf}) \Rightarrow \text{conf} \rightarrow (\text{arr } a \ b) \rightarrow (\text{arr } [a] \ [b]) \\ \text{parMap } \text{conf } f &= \text{parEvalN } \text{conf } (\text{repeat } f) \end{aligned}$$
Figure C 4: Definition of *parMap*.Figure C 5: Schematic depiction of *parMapStream*.
$$\begin{aligned} \text{parMapStream} &:: (\text{ArrowParallel } \text{arr } a \ b \ \text{conf}, \text{ArrowChoice } \text{arr}, \text{ArrowApply } \text{arr}) \Rightarrow \\ &\quad \text{conf} \rightarrow \text{ChunkSize} \rightarrow \text{arr } a \ b \rightarrow \text{arr } [a] \ [b] \\ \text{parMapStream } \text{conf } \text{chunkSize } f &= \text{parEvalNLazy } \text{conf } \text{chunkSize } (\text{repeat } f) \end{aligned}$$
Figure C 6: Definition of *parMapStream*.
$$\begin{aligned} \text{shuffle} &:: (\text{Arrow } \text{arr}) \Rightarrow \text{arr } [[a]] \ [a] \\ \text{shuffle} &= \text{arr } (\text{concat} \circ \text{transpose}) \\ \text{unshuffle} &:: (\text{Arrow } \text{arr}) \Rightarrow \text{Int} \rightarrow \text{arr } [a] \ [[a]] \\ \text{unshuffle } n &= \text{arr } (\lambda xs \rightarrow [\text{takeEach } n \ (\text{drop } i \ xs) \mid i \leftarrow [0..n-1]]) \\ \text{takeEach} &:: \text{Int} \rightarrow [a] \rightarrow [a] \\ \text{takeEach } n \ [] &= [] \\ \text{takeEach } n \ (x:xs) &= x : \text{takeEach } n \ (\text{drop } (n-1) \ xs) \end{aligned}$$
Figure C 7: Definitions of *shuffle*, *unshuffle*, *takeEach*.
$$\begin{aligned} \text{lazy} &:: (\text{Arrow } \text{arr}) \Rightarrow \text{arr } [a] \ [a] \\ \text{lazy} &= \text{arr } (\lambda \sim (x:xs) \rightarrow x : \text{lazy } xs) \\ \text{rightRotate} &:: (\text{Arrow } \text{arr}) \Rightarrow \text{arr } [a] \ [a] \\ \text{rightRotate} &= \text{arr } \$ \lambda \text{list} \rightarrow \text{case list of} \\ &\quad [] \rightarrow [] \\ &\quad xs \rightarrow \text{last } xs : \text{init } xs \end{aligned}$$
Figure C 8: Definitions of *lazy* and *rightRotate*.

```

lazyzip3 :: [a] → [b] → [c] → [(a,b,c)]
lazyzip3 as bs cs = zip3 as (lazy bs) (lazy cs)
uncurry3 :: (a → b → c → d) → (a, (b,c)) → d
uncurry3 f (a, (b,c)) = f a b c
threetotwo :: (Arrow arr) ⇒ arr (a,b,c) (a, (b,c))
threetotwo = arr $ λ~(a,b,c) → (a, (b,c))

```

Figure C 9: Definitions of *lazyzip3*, *uncurry3* and *threetotwo*.

```

farmChunk :: (ArrowParallel arr a b conf, ArrowParallel arr [a] [b] conf,
  ArrowChoice arr, ArrowApply arr) ⇒
  conf → ChunkSize → NumCores → arr a b → arr [a] [b]
farmChunk conf chunkSize numCores f =
  unshuffle numCores >>>
  parEvalNLazy conf chunkSize (repeat (mapArr f)) >>>
  shuffle

```

Figure C 10: Definition of *farmChunk*.

```

ringSimple :: (Trans i, Trans o, Trans r) ⇒ (i → r → (o,r)) → [i] → [o]
ringSimple f is = os
  where (os, ringOuts) = unzip (parMap (toRD $ uncurry f) (zip is $ lazy ringIns))
        ringIns = rightRotate ringOuts
toRD :: (Trans i, Trans o, Trans r) ⇒ ((i,r) → (o,r)) → ((i, RD r) → (o, RD r))
toRD f (i, ringIn) = (o, release ringOut)
  where (o, ringOut) = f (i, fetch ringIn)
rightRotate :: [a] → [a]
rightRotate [] = []
rightRotate xs = last xs : init xs
lazy :: [a] → [a]
lazy~(x:xs) = x : lazy xs

```

Figure C 11: Eden's definition of the *ring* skeleton.

```

parEval2 :: (ArrowChoice arr,
  ArrowParallel arr (Either a c) (Either b d) conf) ⇒
  conf → arr a b → arr c d → arr (a,c) (b,d)
parEval2 conf f g =
  arr Left *** (arr Right >>> arr return) >>>
  arr (uncurry (:)) >>>
  parEvalN conf (replicate 2 (f +++ g)) >>>
  arr partitionEithers >>>
  arr head *** arr head

```

Figure C 12: Definition of *parEval2*.



*Arrows for Parallel Computations*

41

```
prMMTr m1 m2 = [[sum (zipWith (*) row col) | col ← m2] | row ← m1]
splitMatrix :: Int → Matrix → [[Matrix]]
splitMatrix size matrix = map (transpose ∘ map (chunksOf size)) $ chunksOf size $ matrix
matAdd = chunksOf (dimX x) $ zipWith (+) (concat x) (concat y)
```

Figure C 13: Definition of *prMMTr*, *splitMatrix* and *matAdd*.