

# RISE & Shine: Language-Oriented Compiler Design

Michel Steuwer\* Thomas Köhler† Bastian Köpcke‡ Federico Pizzuti\*

\*University of Edinburgh, Scotland, UK †University of Glasgow, Scotland, UK ‡University of Münster, Germany  
Email: michel.steuwer@ed.ac.uk, thomas.koehler@thok.eu, bastian.koepcke@wwu.de, federico.pizzuti@ed.ac.uk

**Abstract**—The trend towards specialization of software and hardware — fueled by the end of Moore’s law and the still accelerating interest in domain-specific computing, such as machine learning — forces us to radically rethink our compiler designs. The era of a universal compiler framework built around a single one-size-fits-all intermediate representation (IR) is over. This realization has sparked the creation of the MLIR compiler framework that empowers compiler engineers to design and integrate IRs capturing specific abstractions. MLIR provides a generic framework for SSA-based IRs, but it doesn’t help us to decide how we should design IRs that are easy to develop, to work with and to combine into working compilers.

To address the challenge of IR design, we advocate for a *language-oriented compiler design* that understands IRs as formal programming languages and enforces their correct use via an accompanying type system. We argue that programming language techniques directly guide extensible IR designs and provide a formal framework to reason about transforming between multiple IRs. In this paper, we discuss the design of the Shine compiler that compiles the high-level functional pattern-based data-parallel language RISE via a hybrid functional-imperative intermediate language to C, OpenCL, and OpenMP.

We compare our work directly with the closely related pattern-based LIFT IR and compiler. We demonstrate that our language-oriented compiler design results in a more robust and predictable compiler that is extensible at various abstraction levels. Our experimental evaluation shows that this compiler design is able to generate high-performance GPU code.

**Index Terms**—Compiler Design, Intermediate Representation

## I. INTRODUCTION

The end of Moore’s law and Dennard’s scaling has opened the door to *a new golden age for computer architecture* [11] that is characterized by specialization of hardware, which we already see in the diverse landscape of AI and ML accelerators.

Together with the specialization in hardware, we observe an accelerating trend of specialized software solutions as well, again most prominently in the domain of machine learning with popular frameworks such as TensorFlow and PyTorch.

To exploit the tremendous efficiency gains of specialized hardware, we need *specialized compilers* capable of translating the specialized software to the hardware by employing optimizations depending on the software domains and hardware capabilities. Gone are the days of a one-size-fits-all compiler with a single intermediate representation (IR) sufficient to optimize for the few standard hardware architectures of interest.

These observations sparked the creation of the MLIR [16] compiler framework as a natural evolution of the well-known LLVM [15] compiler framework that embraced the idea of a single static assignment (SSA)-based IR and with it managed to unify community development efforts in the compiler community at an unprecedented scale.

MLIR — in contrast to LLVM — embraces diversity and specialization of IRs and their optimizations. With only few core constraints on the IR designs, most notably the insistence on SSA as a formal foundation, MLIR has already proven to be a versatile framework for expressing various IRs<sup>1</sup>. This includes traditional generic IRs (such as the LLVM IR itself), IRs reflecting specific programming models (such as OpenMP and TensorFlow), IRs specialized towards particular styles of optimizations (such as the polyhedral model), IRs reflecting specific hardware features (such as vectorization and GPU-specific features), all the way to IRs for hardware circuit design.

But besides its core foundations, MLIR provides little guidance on how to design *good* IRs that are easily extended and easy to work with, which are robust by ruling out ill-formed programs, and which compose well when integrated in full compilers. MLIR provides a framework for designing compilers as compositions of various SSA-based IRs, but what should be our mental framework for designing the IRs themselves?

In this paper, we argue that we should look at programming language design for inspiration. Of course, this observation is not new, but we believe that this paper adds a new perspective by providing insights into our experience of following this approach. We present our experience of designing the optimizing Shine compiler for RISE — a functional data-parallel programming language in the spirit of LIFT [31, 32]. RISE builds on a small functional core language that is enriched with data-parallel patterns such as map and reduce suitable for expressing numerical computations over tensors relevant in many domains ranging from machine learning to scientific computing. The functional and pattern-based design makes it easy to exploit high-level optimization opportunities via rewriting and to generate high-performance code as explored before in the context of LIFT [9, 24] and RISE [10, 14].

To summarize, this paper makes the following contributions:

- We advocate a language-oriented IR and compiler design by reporting our experience of engineering the Shine compiler and discussing its design (Section III);
- we describe the benefits of our compiler design: a clear separation of concerns between optimizing and code generation (Section IV), formalizing of invariants and assumptions about IRs in type systems (Section V), and its extensibility at various levels in the compiler (Section VI);
- we present an experimental evaluation demonstrating the quality of the generated code (Section VII).

<sup>1</sup><https://mlir.llvm.org/docs/Dialects/>

## II. BACKGROUND IN IR AND COMPILER DESIGN

Compiler IRs have been studied extensively before. In the community of optimizing compilers for imperative languages, SSA [23] — developed in the late 1980s at IBM research [2, 27] — has by now been established as the standard form for IRs. SSA makes *def-use-chains* explicit and guarantees that *defs* are introduced before they are *used*. Since the mid-1970s, the functional community used lambda calculus (introduced in the 1930s by Alonzo Church) as a compiler IR. The *Lambda Papers* series even advocated the flexibility of lambda calculus to model non-functional languages [29, 30].

In the mid/late 1990s Kelsey and Appel pointed out a direct correspondence between SSA and the functional lambda calculus representations [3, 13]. Despite this fundamental correspondence, the functional and imperative compiler communities have continued to develop largely independently.

The rise of machine learning in the last decade has sparked interest in domain-specific compilers and their IRs, specifically for numerical computations over tensors — multidimensional arrays. These specialized compilers such as TensorFlow [1], PyTorch [20], or TVM [8] often use a graph-based representation. These systems have developed into complex optimizing compilers having taken on inspirations from related compilers such as Halide [22] and LIFT [31, 32]. LIFT builds on a tradition of similar functional languages and compilers that existed before, such as SaC [28]. More have emerged recently, including Accelerate [7] and Futhark [12] as well as Dex [21] by Google research.

An advantage of the functional representation is that optimizations are naturally expressed via rewriting allowing the automatic exploration of optimizations for example by stochastic search as explored by LIFT [24, 31]. Stratego [5] and more recently ELEVATE [10] show how to describe complex program transformations as composition of rewrites expressed in *strategy languages* that provide a more formal treatment of the *scheduling languages* found in Halide and TVM.

To accommodate the rising need for specialized IRs, MLIR [16] provides a common framework for designing IRs and transformations between them. The different IRs, called *dialects*, must follow the SSA form. But in contrast to LLVM’s IR, the awkward  $\phi$ -nodes are replaced with so-called *regions* that allow for directly representing nested structures, such as control flow with multiple branches, e.g., an *if-then-else* operation. MLIR allows for a broad range of IRs to be represented and provides itself little guidance on how to design dialects that are well-behaved, that is, dialects that: 1) providing a clear purpose; 2) have formally checked invariants and assumptions; 3) are easily extensible.

In this paper, we provide a perspective on how to design IRs that have these positive properties. We share our experience in developing the Shine compiler that composes a LIFT-like functional IR with a hybrid functional-imperative IR for compiling high-level programs to high-performance code.

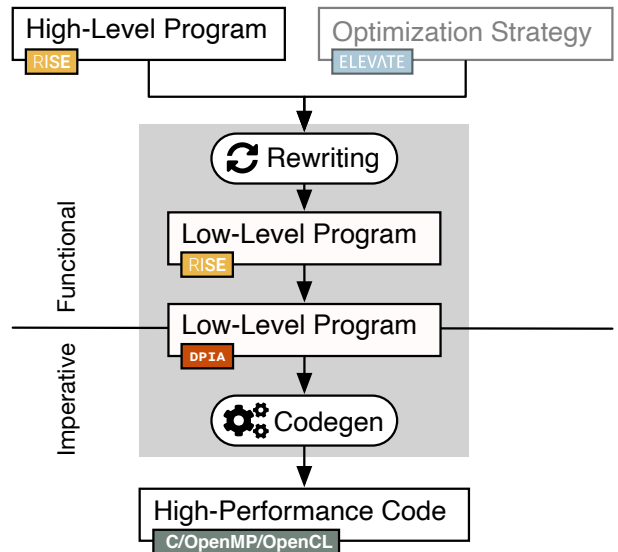


Fig. 1: Overview of the language-oriented designed compiler Shine: *High-level programs* expressed in the functional language RISE are rewritten to encode all major optimization and implementation choices. The resulting *low-level program* is translated into DPIA — a language combining functional and imperative aspects, from which *high-performance code* is generated. The language-oriented design results in a clear separation of concerns (optimizing vs. code generation), it simplifies the formalization of invariants and assumptions about the IRs in their type systems, and it’s easily extensible by introducing abstractions at multiple levels in the compiler.

## III. SHINE: A LANGUAGE-ORIENTED COMPILER

Figure 1 shows an overview of the Shine compiler. The overall design follows the compiler described by Hagedorn et al. in [10] where an optimization strategy written in a *strategy language* (aka, scheduling language) called ELEVATE specifies the optimizations to be applied to the input program. ELEVATE is described in detail in [10] and we will not discuss it further in this paper, but we highlight that it allows for experts (human or machine) to directly control the optimizations to be performed.

The input program of the Shine compiler is written in the functional data-parallel language RISE that uses a restricted form of *dependent types* to track the size of multi-dimensional arrays in the type. This follows our language-oriented design principle in that this information is embedded into the type system of the IR rather than being represented as separate meta-data. This has the main advantage that we have a formal account of the structure of the meta-data (here tracking array lengths) allowing us to ensure its consistency by the soundness of the type system, for example, the type system accounts for the basic fact that variables referred to in the types must be well-scoped.

The process of compiling a high-level RISE program to high-performance code is shown in Figure 1. The process is broken into two steps, each with a corresponding language and type system serving as the IR.

First, the functional *high-level program* is transformed via rewriting into a *low-level program* that encodes optimization and implementation decisions. The ELEVATE optimization strategy, given as an input to the compiler, describes these decisions, such as: Should we fuse multiple patterns to avoid intermediate buffers? In which address space should we allocate intermediate buffers? Should we perform map patterns in parallel or sequential? In this rewriting step, choices for these decisions are directly encoded, resulting in a functional *low-level program*.

The remaining steps translate the functional low-level program into an imperative low-level program. For this, we introduce a new typed language called `DPiA` as IR that combines functional and imperative aspects while preventing simultaneous sharing and mutation similar to Rust. After translating the functional low-level RISE program into a functional `DPiA` program, we gradually translate it into an imperative program using a formal translation. This translation preserves the implementation and optimization choices made before and does not make significant implementation choices itself. Finally, *high-performance code* is generated (C, OpenMP, or, OpenCL depending on the implementation choices made).

#### IV. CLEARLY SEPARATING OPTIMIZING FROM CODE GENERATION

One main principle observed in the Shine compiler is the clear separation of IRs for optimizing and code generation. In this design, two languages (RISE and `DPiA`) are composed, each serving as the IR for one task: all optimizations and major implementation decisions are performed on RISE; the code generation process of translating the functional to an imperative program is performed in `DPiA`.

Keeping these two fundamental tasks separated has the key advantage that the IR for optimizing is kept simple and free of unnecessary low-level details. These are only added after all optimization decisions are encoded in the functional program.

To understand the optimization and code generation process of the Shine compiler, we will follow an easy-to-understand running example: matrix-vector-multiplication (Listing 1). This functional program describes the computation algorithmically without committing to a particular implementation strategy: for each row of the matrix `M`, we compute the dot-product with the input vector `x`. The dot-product is expressed in lines 5–7

```

1 def mv = depFun((n: Nat, m: Nat) =>
2   fun(M: Array[n, Array[m, f32]] =>
3     fun(x: Array[m, f32] =>
4       M |> map(fun(row =>
5         zip(row)(x) |>
6           map(fun(ax => fst(ax) * snd(ax))) |>
7             reduce(add)(0.0f) )) )) )

```

Listing 1: Matrix-Vector-Multiplication expressed as a high-level program in RISE. No optimization or implementation choices have been made yet, there are many ways to compile this program to high-performance code.

```

E := x | 0.0f |                               variables and literals
     fun(x => E) |                               function abstraction
     E |> E | E(E) |                             function application
     depFun(x: K => E) |                         dependent fun. abstraction
     E(N) | E(DT) | E(A) |                     dependent fun. application
     map | reduce | reduceSeq | zip | ...       primitives

```

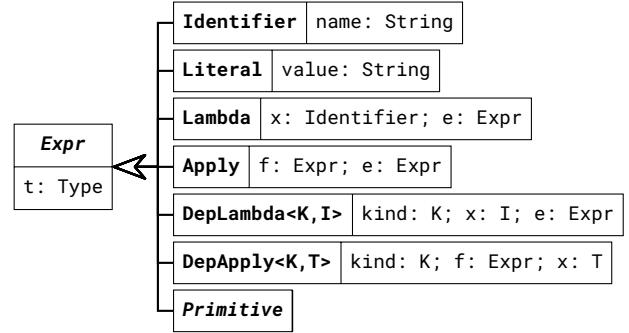


Fig. 2: Grammar of RISE expressions (above) and corresponding diagram of classes (below) representing them.

by composition of the `zip` primitive that aligns the matrix row and the vector element wise, followed by the `map` primitive that multiplies each aligned pair, before the resulting array is summed up using the `reduce` primitive. In RISE, sizes of multi-dimensional arrays can be tracked symbolically in their types. For this, we introduce a *dependent function* in line 1 that abstracts over the type-level size values in the same way as ordinary functions abstract over computational values. The introduced variables `n` and `m` are now allowed to appear in the *types* of the nested expression. In a non-language-oriented IR design, such information is often modeled as meta-data without a clear understanding of scoping rules and how it interacts with the computational operations of the IR. Next, let us investigate the RISE language itself.

##### A. RISE expressions, types, and primitives

From a users’ perspective, RISE shares many common features with the LIFT IR, but their implementations differ significantly. The LIFT implementation separates expressions and function declarations and lacks a formalized type system, in particular LIFT lacks the concept of a function type. In contrast, RISE unifies all language constructs under a single `Expr` superclass. This simplified design follows the usual implementation of languages in the functional community by using an *algebraic data type (ADT)* to represent the various language constructs. ADTs model data in a structured way by organizing it in a finite set of alternative cases, where each case is represented as a `struct` containing multiple fields. ADTs are a perfect fit to represent grammars, such as RISE’s grammar shown at the top of Figure 2. Support for ADTs is directly built into many functional languages, but support has recently also been added in non-functional languages, e.g., they are known as `enum` in Rust and Swift and as `std::variant` in C++. A straightforward way to encode ADTs in an object-oriented language is to build a flat class hierarchy, as shown at the bottom of Figure 2.

$T := t \mid DT \mid$  type variables & data types  
 $T \rightarrow T \mid (x: K) \rightarrow T$  function types  
 $DT := f32 \mid \dots \mid$  scalar types  
 $Array[N, DT] \mid Tuple[DT, DT]$  array & tuple types  
 $N := 0 \mid 1 \mid \dots \mid N + N \mid N * N \mid \dots$  natural numbers  
 $A := Global \mid Local \mid Private$  OpenCL address spaces  
 $K := Nat \mid DataType \mid AddrSp$  kinds

```

map: {n: Nat} -> {s: DataType} -> {t: DataType} ->
(s -> t) -> Array[n, s] -> Array[n, t]
reduce: {n: Nat} -> {t: DataType} ->
(t -> t -> t) -> t -> Array[n, t] -> t
zip: {n: Nat} -> {s: DataType} -> {t: DataType} ->
Array[n, s] -> Array[n, t] -> Array[n, Tuple[s, t]]

```

Listing 2: Selection of RISE functional data-parallel primitives

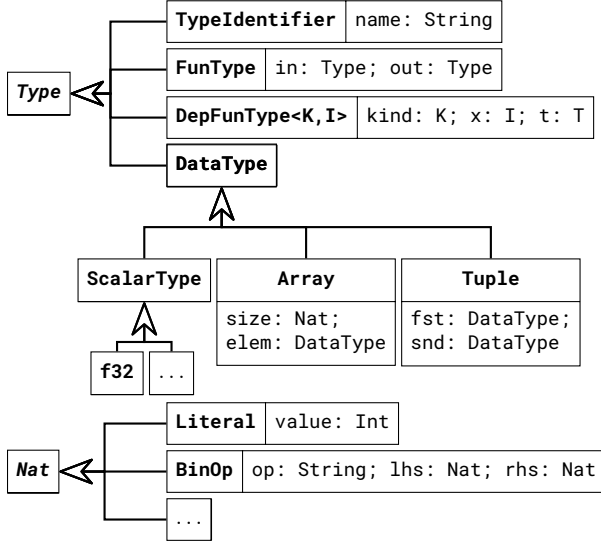


Fig. 3: Grammar of RISE types and type-level values (above) and diagram of classes (below) representing them.

The Expr class is abstract with seven subclasses modeling the language constructs, such as: Lambda and Apply to model function abstraction (aka, lambdas) and application, DepLambda/Apply to model function abstraction/application over variables at the type level (e.g, for reasoning about the length of arrays), and finally, Primitive to represent primitives, such as map and reduce.

Figure 3 shows the grammar and corresponding class hierarchies of RISE types. Type level values are organized into distinct and interconnected classes following the formalization given by the grammar and the formal typing rules (not shown in this paper, but described in [4, 9]). DataTypes are kept distinct from general types and represent types that can be stored in memory. As we compile to GPUs, this design carefully avoids the challenge of storing functions (or closures) in memory, enforcing an important invariant of our IR.

Array types track their length with the member size that is a natural number and forms a distinct category of expressions represented by the Nat class and subclasses.

Finally, Listing 2 shows some important high-level data-parallel primitives modeled as functions. We use a functional notation for their types, i.e., every argument is separated by  $\rightarrow$ . For example, map expects 5 arguments, 3 at the type-level: a natural number  $n$ , 2 data types  $s$  and  $t$ ; and 2 ordinary arguments: a function and an array to whose elements the function is applied to produce the output array. Parameters in curly braces are implicit and automatically inferred.

### B. Optimizing RISE via rewriting

Optimizing is the primary focus of RISE, and it is clearly separated from compiling the functional abstractions away. Translation to imperative constructs happens in later stages.

The rewrite rules used in the Shine compiler follow closely the rules introduced by LIFT, for example, three algorithmic rules for splitting and fusing map and reduce:

```

map(f) ↦ split(n) >> map(map(f)) >> join
map(f) >> map(g) ↦ map(f >> g)
map(f) >> reduce(fun(acc, y => acc ⊕ y), init)
↦ reduceSeq(fun(acc, y => acc ⊕ f(y)), init)

```

These rules encode algorithmic optimization *choices* that when applied to an expression directly encode that choice in the rewritten expression. This becomes even more clear for rules translating a high-level RISE primitive into a low-level implementation-specific primitive. For example, the following rules provide different options to implement the high-level map primitive in the OpenCL programming model:

```

map ↦ mapSeq           map ↦ mapGlobal
map ↦ mapWorkGroup    map ↦ mapLocal

```

Applying one of these rules to a map primitive encodes the explicit choice that this primitive should be implemented either sequentially or in one of three different parallel ways, each exploiting different aspects of the GPU.

Rewrite rules transforming RISE are expressed in ELEVATE [10] a language for composing rewrite rules into larger *optimization strategies*. In this design, rewrite rules are functions taking a RISE expression as input and returning the transformed expression or a failure state if the rewrite rule could be applied. An ELEVATE optimization strategy that describes a particular composition of rewrite rules corresponds to a *schedule* in systems such as TVM or Halide describing precisely how the high-level RISE program should be optimized and implemented.

### C. Optimizing Matrix-Vector-Multiplication

There are many choices to be made when deciding how to optimize the matrix-vector-multiplication example from Listing 1. A key idea of optimizing by rewriting in the Shine compiler is to expose these choices rather than make them internally.

Listing 3 shows one possible (and for illustration purposes simple) way to optimize. This ELEVATE optimization strategy describes a sequence of rewrite steps that transforms the high-level description of matrix-vector-multiplication into the low-

```

splitJoinMap    ~@~ outermost(isMap)    ~;~
toMapWorkGroup ~@~ outermost(isMap)    ~;~
toMapLocal     ~@~ outermost(isMap)    ~;~
fuseReduceMap  ~@~ every(isReduce)     ~;~
toReduceSeq    ~@~ every(isReduce)

```

Listing 3: One possible way to optimize Matrix-Vector-Multiplication encoded as an ELEVATE optimization strategy.

```

1 def mvOpt = depFun((n: Nat, m: Nat) =>
2   fun(M: Array[n, Array[m, f32]] =>
3     fun(x: Array[m, f32] =>
4       M |> split(s) |> mapWorkGroup(fun(rows =>
5         rows |> mapLocal(fun(row =>
6           zip(row)(x) |>
7             reduceSeq(Private)(fun(acc, ax =>
8               acc + (fst(ax) * snd(ax))))(0.0f) ))
9         )) |> join
10      )) )

```

Listing 4: Optimized Matrix-Vector-Multiplication in RISE.

level version shown in Listing 4. The outermost `map` is split into two maps (using the `splitJoinMap` rule) that are then lowered into two specific versions of map reflecting the OpenCL parallelism model. The `reduce` and `map` primitives describing the dot product computation are fused into a single reduction (using the `fuseReduceMap` rule). This reduction can no longer be parallelized (as the operator is not associative), but we avoid the need for an intermediate buffer and two separate loops.

### Summary

In this section, we have discussed the design of the RISE language that is used in the Shine compiler for explicitly encoding optimization and implementation choices. This clear purpose heavily influences the design of the language: optimizations are expressed as compositions of rewrite rules, allowing them to be easily extended and externally controlled; to enable rewriting, the IR is functional and free of side effects to be referentially transparent (i.e., to allow any expression to be replaced by an equivalent expression).

Deliberately, RISE does not have imperative features or concepts, such as assignments into memory, or `for` loops. This still leaves a large gap to close between the optimized RISE program and the targeted imperative programming models, such as C, OpenMP, or OpenCL. To translate the functional to imperative code, we introduce a separate dedicated language called DPIA that does provide functional and imperative concepts and is, therefore, suited to serve for the further code generation process. While existing functional solutions, such as LIFT, have RISE-like languages, are missing a dedicated IR for code generation, such as DPIA, and, therefore, combine optimizing and code generation in one step, complicating both steps and the overall compiler design.

## V. TYPE SYSTEMS FOR FORMALIZING INVARIANTS AND ASSUMPTIONS

Each compiler IR has invariants and assumptions that must hold for optimizations and translations to work as expected. For example, a polyhedral-specific IR must ensure that array indices are affine for polyhedral optimizations to be valid. In this section, we will discuss how a language-oriented view helps to formalize such invariants and assumptions in the type system of the language used as the IR.

We already discussed in Section IV that RISE separates data types whose values are stored in memory from function types, enforcing an important invariant and ruling out programs that we are unable to compile into efficient GPU code. We also formulated the clear goal, that all optimization and implementation decisions have to be encoded directly into the RISE program. This is a crucial assumption we make in the further compilation process. But how do we enforce it?

It is easy to check that implementations have been chosen for high-level primitives, for example, it is easy to check that all map primitives have been replaced with their implementation-specific counterparts (e.g., `mapSeq` or `mapGlobal`). But there is a crucial hidden choice that cannot be overlooked: memory. Let's consider for example the following RISE program:

```

depFun((n: Nat, m: Nat) =>
  fun(M: Array[n, Array[m, f32]] =>
    M |> mapWorkGroup(fun(row =>
      row |> mapLocal(f) |> mapLocal(g) )))

```

Listing 5: RISE program without choice of temporary memory.

For every element in every row of the matrix `M`, first the function `f` is applied and then the function `g`. The parallelization strategy is clearly described here and also the fact that `f` and `g` will be computed in two separate steps rather than a single one. But this leaves the choice of where to allocate the intermediate memory. On a GPU, there are different address spaces (e.g., local/shared vs global memory) with vastly different size and performance characteristics. In LIFT, this choice is already modeled via specific primitives such as `toLocal` and `toGlobal` [32], but making this choice explicitly is not enforced. In the following, we introduce the DPIA language, and its type system that formalizes the intuition that everywhere where we need to write to memory the address space choice has been made. Furthermore, DPIA combines functional and imperative aspects to facilitate the translation of the optimized functional program to imperative high-performance code.

### A. DPIA phrases, types, and primitives

DPIA is a variation of Reynolds's idealized ALGOL [4, 25] and aims to integrate functional and imperative concepts in a single language. For this, we separate our program *phrases* into three categories: (functional) *expressions*, (imperative) *commands* (like C statements), and (imperative) *acceptors*. One can think of an acceptor as a pointer that we can manipulate and ultimately use for writing to a memory location.

```

P := x | 0.0f |                               variables and literals
    fun(x => P) |                               function abstraction
    P |> P | P(P) |                             function application
    depFun(x: K' => P) |                         dependent fun. abstraction
    P(N) | P(DT) | P(A) |                       dependent fun. application
    mapWorkGroup|reduceSeq|...                 functional primitives
    P=P|(|;)|new|parForWorkGroup|...          imperative primitives

T' := t | T' → T' | (x:K) → T' |              type var. & function types
    T' × T' |                                  phrase pair type
    Exp[DT, RW] |                              expression type
    Acc[DT] |                                  acceptor type
    Comm                                       command type
RW := Rd | Wr                                 read-write annotations
K' := K | ReadWrite                          kinds: read-write & RISE kinds

```

Fig. 4: Grammar of DPIA phrases, types, and type-level values.

Figure 4 shows the grammar of DPIA phrases and types. The language looks similar to RISE and in fact uses RISE’s functional language constructs and data types. New are the imperative constructs, such as assignment ( $P=P$ ). The type system reflects the separation into expressions ( $\text{Exp}[DT, RW]$ ), acceptors ( $\text{Acc}[DT]$ ), and commands ( $\text{Comm}$ ). (Dependent) functions and pairs can freely combine phrases of all categories. The expression type has a  $\text{ReadWrite}$  annotation used for checking that an input program has encoded all choices about memory address spaces explicitly, as we will discuss in Section V-B.

Listing 6 and 7 show a selection of DPIA primitives. In RISE, we introduced primitives with a function type. In contrast, in DPIA primitives are fully applied values. For example, in RISE  $\text{mapSeq}(f)$  represents the function application of  $\text{mapSeq}$  to  $f$ . The equivalent program in DPIA, must use a lambda:  $\text{fun}(x \Rightarrow \text{mapSeq}(f, x))$ . Insisting on fully applied primitives simplifies the translation and code generation process, while allowing partially applied primitives (such as  $\text{map}(f)$ ) simplifies the specification of rewrite rules. With two separate IRs, we can choose the most convenient style for each task.

The functional primitives in Listing 6 only contain low-level variations of the high-level  $\text{map}$  and  $\text{reduce}$  primitives, as for programs at this stage, all implementation choices must have been made. Some functional primitives, such as  $\text{zip}$ ,  $\text{join}$ , and  $\text{split}$  will always be fused into successive primitives and, therefore, remain unchanged. There are also low-level primitives such as indexing into arrays ( $\text{idX}$ ) and  $\text{toMem}$  which we will discuss in the next section.

Listing 7 shows a selection of DPIA’s imperative primitives and their types. These are commands, such as writing to memory via an  $\text{assignment}$ ,  $\text{sequencing}$  commands, memory allocation ( $\text{new}$ ), and sequential and parallel  $\text{for}$  loops.  $\text{zipAcc1/2}$  and  $\text{joinAcc}$  represent computations over acceptors, for example, treating a one-dimensional array as a two-dimensional one ( $\text{joinAcc}$ ). Eventually, these computations will correspond to pointer manipulations in the generated code.

### B. Enforcing Presence of Necessary Address Space Choices

In Listing 5 we introduced an example of a RISE program where a necessary choice to clarify the address space of a temporary memory buffer was missing. If we attempt to compile

```

mapLocal(n: Nat, s: DataType, t: DataType,
  f: Exp[s,Rd] -> Exp[t,Wr],
  x: Exp[Array[n,s],Rd]): Exp[Array[n,t],Wr]
reduceSeq:(n: Nat, a: AddrSp, s: DataType, t: DataType,
  f: Exp[t,Rd] -> Exp[s,Rd] -> Exp[t,Wr],
  init: Exp[t,Wr], x: Exp[Array[n,s],Rd]): Exp[t,Rd]
zip:(n: Nat, s: DataType, t: DataType, w: ReadWrite,
  lhs: Exp[Array[n,s],w],
  rhs: Exp[Array[n,t],w]): Exp[Array[n,Tuple[s,t]],w]
join:(n: Nat, m: Nat, t: DataType, w: ReadWrite,
  x: Exp[Array[n,Array[m,t]],w]): Exp[Array[n*m,t],w]
split:(n: Nat, m: Nat, t: DataType, w: ReadWrite,
  x: Exp[Array[n*m,t],w]): Exp[Array[m,Array[n,t]],w]

toMem:(a: AddrSp, t: DataType, x: Exp[t,Wr]): Exp[t,Rd]
idx:(n: Nat, t: DataType,
  i: Exp[Idx[n],Rd], arr: Exp[Array[n,t],Rd]): Exp[t,Rd]

```

Listing 6: Selection of DPIA functional primitives

```

assign:(t: DataType, lhs: Acc[t], rhs: Expr[t, Rd]): Comm
seq:(c1: Comm, c2: Comm): Comm
new:(a: AddrSp, t: DataType,
  body: (Exp[t,Rd] × Acc[t]) -> Comm): Comm
for:(n: Nat, body: Exp[Idx[n],Rd] -> Comm): Comm
parForLocal(n: Nat, t: DataType,
  out: Acc[Array[n,t]],
  body: Exp[Idx[n],Rd] -> Acc[t] -> Comm): Comm

zipAcc1:(n: Nat, s: DataType, t: DataType,
  array: Acc[Array[n,Tuple[s,t]]]: Acc[Array[n,s]])
zipAcc2:(n: Nat, s: DataType, t: DataType,
  array: Acc[Array[n,Tuple[s,t]]]: Acc[Array[n,t]])
joinAcc:(n: Nat, m: Nat, t: DataType,
  array: Acc[Array[n*m,t]]): Acc[Array[n,Array[m,t]])

```

Listing 7: Selection of DPIA imperative primitives

this program, we have to make a decision on behalf of the user. We want to avoid such situations, and DPIA’s type system formalizes this: when translating a program from RISE to DPIA the type system checks the consistency of all  $\text{ReadWrite}$  annotations and rejects programs with inconsistent annotations. Let’s revisit the example from Listing 5, after it has been translated to DPIA:

```

depFun((n: Nat, m: Nat) =>
  fun(M: Exp[Array[n, Array[m, f32]], Rd] =>
    mapWorkGroup(n, Array[m, f32], Array[m, f32],
      fun(row => mapLocal(m, f32, f32, g,
        mapLocal(m, f32, f32, f, row))),
    M )))

```

The translation process from low-level RISE to functional DPIA is straightforward, as there exists a corresponding DPIA primitive for each low-level primitive in RISE.

The program should not type check in DPIA as a choice of address space is missing. Let us understand why by looking at the crucial part of the program:

```

mapLocal(m, f32, f32, g,
  // expected:                               Exp[Array[m, f32], Rd] ✗
  mapLocal(m, f32, f, row) : Exp[Array[m, f32], Wr])

```

As indicated by the comment, we can see that the type of the second `mapLocal` does not match the type expected by the first `mapLocal`. The precise type of `mapLocal` is given in Listing 6. Clearly, the `ReadWrite` annotations do not match: we expect a value that we can read from memory (as indicated by `Rd`), but instead we have been given a value that first has to be written to memory (as indicated by `Wr`) before we can read it.

The `ReadWrite` annotations are introduced in the translation process from RISE to DPIA and the functional primitives in Listing 6 are explicitly annotated with them. Some primitives, such as `zip`, are polymorphic over `ReadWrite` annotations, i.e., their annotation depends on the context they are used in. For these primitives, a simple inference is performed.

There exists only one primitive to convert an expression that needs to be written to memory (i.e., with `Wr`) to an expression from which we can read (i.e., with `Rd`): `toMem` which expects the address space to write into as an argument.

Therefore, to fix our program, we need to inject a `toMem` in between the two `mapLocal`s. This choice has to be encoded in the RISE program, e.g., via an appropriate rewrite rule, before we translate to DPIA. Once we are in DPIA, we can only check that address space annotations are consistent.

After adding `toMem` in the RISE program and translating to DPIA we see that the type checking succeeds:

```
mapLocal(m, f32, f32, g,
// expected: Exp[Array[m, f32], Rd] ✓
toMem(Private, Array[m, f32],
// expected: Exp[Array[m, f32], Wr] ✓
mapLocal(m, f32, f, row) : Exp[Array[m, f32], Wr]
) : Exp[Array[m, f32], Rd] )
```

It is important to note that `toMem` only accepts arguments that are not yet written to memory, as indicated by the `Wr` annotation on its input. Otherwise, we would have to make a decision on *how* to copy the value from one memory location to another. But there are many ways to copy, for example, an array: sequentially, vectorized, or in parallel using threads? As we refuse to make such choices in DPIA, we reject such programs and insist that the choice on how to perform the copy must be encoded in RISE explicitly.

### C. Translating Functional into Imperative Programs

Now that we are confident that all implementation decisions are encoded in the functional DPIA program, we discuss how it is translated into a program using DPIA's imperative features. For example, we want to translate a primitive such as `reduceSeq` into a `for` loop.

This translation process is performed by two intertwined translation functions, shown in Listing 8 and 9. The *acceptor translation* `accT` takes a functional expression that needs to be written to memory (i.e., with `Wr`) plus an acceptor representing the memory to write into. The *continuation translation* `conT` takes expressions that we can read from (i.e., with `Rd`) plus a *continuation* function that knows how to continue the translation once we have translated the current expression. Both translations return an imperative command.

```
def accT(expr: Phrase[Exp[d,Wr]],
output: Phrase[Acc[t]]
): Phrase[Comm] = expr match {
case mapWorkGroup(n, s, t, f, arr) =>
conT(arr, fun(arrT =>
parForWorkGroup(n, t, output, fun((i, o) =>
accT(f(idx(n, s, i, arrT)), o) )))
case mapSeq(n, s, t, f, arr) =>
conT(arr, fun(arrT =>
for(n, fun(i =>
accT(f(idx(n, s, i, arrT)), idxAcc(n, t, i, output) )))
case zip(n, s, t, Wr, lhs, rhs) =>
accT(lhs, zipAcc1(n, s, t, output)) ;
accT(rhs, zipAcc2(n, s, t, output))
case join(n, m, t, Wr, arr) =>
accT(arr, joinAcc(n, m, t, output))
case ...
}
```

Listing 8: Definition of acceptor translation

```
def conT(expr: Phrase[Exp[t,Rd]],
continuation: Phrase[Exp[t,Rd]] -> Phrase[Comm]
): Phrase[Comm] = expr match {
case toMem(a, t, e) =>
new(a, t, fun((tmpAcc, tmpExp) =>
accT(e, tmpAcc) ; continuation(tmpExp) ))
case reduceSeq(n, a, t, s, f, init, arr) =>
conT(arr, fun(arrT =>
new(a, t, fun((accumAcc, accumExp) =>
accT(init, accumAcc) ;
for(n, fun(i =>
accT(f(accumExp, idx(n, s, i, arrT)),
accumAcc) )) ;
conT(accumExp, continuation) )) ))
case join(n, m, t, Rd, lhs, rhs) =>
conT(lhs, fun(lhsT =>
conT(rhs, fun(rhsT =>
continuation(zip(n, s, t, Rd, lhsT, rhsT))))))
case zip(n, s, t, Rd, x) =>
conT(x, fun(xT => continuation(join(n, m, t, Rd, xT)))
case split(n, m, t, Rd, x) =>
conT(x, fun(xT => continuation(split(n, m, t, Rd, xT)))
case fst(s, t, Rd, x) =>
conT(x, fun(xT => continuation(fst(s, t, Rd, xT)))
case snd(s, t, Rd, x) =>
conT(x, fun(xT => continuation(snd(s, t, Rd, xT)))
case ...
}
```

Listing 9: Definition of continuation translation

To start the overall translation process, we allocate *output* memory according to the data type of the value that the functional program computes. When compiling to OpenCL, the results of a kernel must reside in global memory so that we have no choice of address space to make here. With the given *output*, we invoke the `accT` translation. This corresponds to the intuition of translating a program that computes a value functionally and afterwards writes it to memory.

For the matrix-vector-multiplication translated from RISE (Listing 4) to DPIA we invoke `accT` with an output array:

```
mvOptImp = accT(mvOpt, output : Acc[Array[n, f32]])
```

Following the intuition of the acceptor translation, we traverse the functional program backwards, starting with the last primitive; the primitive that writes into the output. In case of the matrix-vector multiplication, the last primitive is `join` with `mapWorkGroup` as its argument. `join` changes our view from a two-dimensional into a one-dimensional array. The acceptor translation indicates that we call `accT` with `join`'s argument (here `mapWorkGroup`) and wrap the output in a `joinAcc`:

```
accT(join(mapWorkGroup(f, arr)), output)
= accT(mapWorkGroup(f, arr), joinAcc(output))
```

The `joinAcc` primitive has the reverse effect on an acceptor to that of `join` on an expression: we transform our view on the output memory, instead of a flat one-dimensional array we treat it as two-dimensional. Then we translate `mapWorkGroup`:

```
accT(mapWorkGroup(f, arr), joinAcc(output))
= cont(arr, fun(arrT =>
  parForWorkGroup(n/s, joinAcc(output), fun((i, o) =>
    accT(f(idx(i, arrT)), o))))))
```

In the imperative program, the code computing the input of `mapWorkGroup` must appear before the code for `mapWorkGroup` itself, therefore, we must continue to translate the input first by using the *continuation translation*. This is the right choice, as we must be able to read from this expression based on the type of `mapWorkGroup`. To describe how the translation continues, we pass along a *continuation* function that will be called once we have translated the input. This function will be given the translated input array (`arrT`) and inside we describe the translation of `mapWorkGroup` itself into a `parForWorkGroup`. This parallel for loop is parameterized with the length of the array, it is mapping over; the output it is writing into; and a function representing the loop body. The loop body has access to the loop index `i` as well as an acceptor `o` that guarantees that each iteration writes to a distinct location in the output array. In the loop body, we invoke the acceptor translation of the function `f` applied to a single value of the (translated) input array by indexing into it and passing the acceptor to write into along.

To translate the full program, we continue the translation process by calling the `accT` and `contT` functions as indicated in Listing 8 and 9 for each primitive, until we have traversed the entire functional program.

The result of the translation process is the imperative DPIA program shown in Listing 10, from which we generate the OpenCL code shown in Listing 11. This final code generation step is small, as the structure of the imperative DPIA program directly corresponds to the OpenCL program. For example, `parForWorkGroup` and `parForLocal` correspond to the two outer loops in line 6 and 8 in the OpenCL code. The remaining gap is to resolve some functional expressions into multi-dimensional array indices. This process is similar to the *views* in LIFT [32] and involves simplifying arithmetic expressions to generate concise indices. The only conceptual difference to LIFT is that in DPIA index computations also happen on acceptors to manipulate the location where we write into memory.

```
1 depFun((n: Nat, m: Nat) =>
2   fun(M:Array[n,Array[m,f32]] => fun(x:Array[m,f32] =>
3     parForWorkGroup(n/s, Array[m,f32], joinAcc(output),
4       fun(wgId, wgOut) =>
5         parForLocal(s,f32, wgOut, fun((lId, lOut) =>
6           new(Private, f32, fun((accumAcc, accumExp) =>
7             accumAcc = 0.0f;
8             for(m, fun(i =>
9               accumAcc = accumExp +
10                fst(idx(i, zip(idx(lId, idx(wgId, split(s,M))), x)))
11                * snd(idx(i, zip(idx(lId, idx(wgId, split(s,M))), x)))
12                )) ; lOut = accumExp ))))))))
```

Listing 10: MV-Mult. after translation into imperative DPIA

```
1 __kernel
2 void mvOptKernel(global float* restrict output,
3   int n, int m, int s,
4   const global float* restrict M,
5   const global float* restrict x) {
6 for (int wgId = get_group_id(0); // parForWorkGroup
7   wgId < n/s; wgId += get_num_groups(0)) {
8 for (int lId = get_local_id(0); // parForLocal
9   lId < s; lId += get_local_size(0)) {
10 float accum; // new
11 accum = 0.0f; // assign
12 for (int i = 0; i < m; i += 1) { // for
13   accum += (M[(i+lId*m)+(m*s*wgId)] * x[i]); }
14   output[lId + (s * wgId)] = accum; }} // assign
```

Listing 11: OpenCL code generated for MV-Mult.

## Summary

In this section, we discussed the DPIA language that is used as an IR in the Shine compiler to translate functional to imperative programs. We have seen, how our language-oriented compiler design enables the formalization of important invariants and assumptions in the type system and prevents ad-hoc implementation choices in the compilation process. Instead, all implementation choices are pushed upwards and must have been encoded explicitly beforehand.

## VI. COMPILER EXTENSIBILITY AT MULTIPLE LEVELS

Extensibility is a crucial consideration in compiler design. By having a slim core language, both RISE and DPIA are easy to extend by adding new primitives. A crucial advantage over purely functional IRs, such as LIFT, is that we can extend DPIA with new imperative primitives, directly capturing code patterns or interfaces in the target programming model.

We illustrate the extensibility by adding support for iterative computations. LIFT proposes an `iterate` primitive, that repeatedly applies a function to an array, passing the output of one iteration as the input of the next. This can be used to describe tree-based reductions and similar iterative algorithms [31].

One efficient way to implement such computations in a C-like programming language is to use double buffering by swapping pointers to two buffers after each iteration. But how would we represent this in DPIA, as there is no support for dealing with pointers directly? To solve this, we add two primitives to DPIA: the functional `iterate` and the imperative `newDoubleBuffer`.



```

1 float buffer1[size]; float buffer2[size];
2 float* in_ptr = input; float* out_ptr = buffer1;
3 unsigned char flag = 1;
4 for (int i = 0; i < k; i += 1) {
5     body(in_ptr, out_ptr);           // body
6     if (i <= (k-1)) {               // swap
7         in_ptr = flag ? buffer1 : buffer2;
8         out_ptr = flag ? buffer2 : buffer1;
9         flag = flag ^ 1;
10    } else {                          // done
11        in_ptr = flag ? buffer1 : buffer2;
12        out_ptr = output; } }

```

Listing 12: C code expressing double buffering.

To start, let’s look at the C code we would like to generate for an iterative computation implemented using double buffering, as shown in Listing 12. First we need to allocate temporary buffers and then initialize two pointers `in_ptr` and `out_ptr` who are pointing to the input and output of each iteration. The `for` loop iterates for a fixed number of `k` iterations and performs the iterative computation in line 5. Afterwards, we need to swap the pointers to prepare for the next iteration. Because we want to avoid the need for unnecessary copies, in the first iteration `in_ptr` points to the input of the overall computation and in the last `out_ptr` to the output. To achieve this, we use a `flag` indicating how we have to swap and an `if` branch to check if the last iteration has been reached.

When adding new primitives, we need to model these implementation aspects in DPIA. For double buffering, we want to avoid exposing pointers directly, and thus we hide the pointer manipulation behind two commands that we expose in DPIA. Listing 13 shows the added `newDoubleBuffer` primitive. It expects multiple arguments: the data types and sizes of the input, output, and temporary buffers, the input array, the output array, and a body function that has access to the double buffer. The body expects four arguments: an acceptor and expression to write/read into/from the current active buffer, and two commands corresponding to the `swap` and `done` code parts from Listing 12. The body may use `swap` and `done` freely. In the final code generation process, these opaque commands are replaced with the code shown in the listing.

Listing 14 shows the translation of the functional `iterate` primitive (List. 13) to imperative DPIA. The `iterate` primitive is translated into a combination of `newDoubleBuffer`, to allocate a double buffer, and `for`, to express the iterative computation. Specifically, the `swap` and `done` commands are used inside the `if`, directly corresponding to the C code in Listing 12.

### Summary

This case study of extensibility highlights two important points: 1) the language-oriented compiler design with multiple single-purpose IRs allows adding abstractions at multiple levels, such as the high-level `iterate` and the low-level `newDoubleBuffer`; 2) the abstractions stand on their own: we did not design an imperative version of `iterate`, but instead designed a double buffer abstraction that can be used in other ways by using the exposed interface of `swap` and `done`.

```

newDoubleBuffer(t: DataType, n: Nat, m: Nat, k: Nat,
input: Exp[Array[m,t],Rd], output: Acc[Array[k,t]],
body: (Acc[Array[n,t] x Exp[Array[n,t],Rd] x Comm x Comm)
-> Comm): Comm

iterate(n: Nat, m: Nat, k: Nat, t: DataType,
body: (1:Nat)->Exp[Array[1*n,t],Rd]->Exp[Array[1,t],Wr],
arr: Exp[Array[(n^k)*m,t],Rd]): Exp[Array[m,t],Wr]

```

Listing 13: Extension to support iterative computations using double buffering.

```

def accT(expr, output) = expr match {
case ...
case iterate(n, m, k, t, body, arr) =>
  conT(arr, fun(arrT =>
    newDoubleBuffer(t, (n^k)*m, m, (n^k)*m,
arr, output, fun((tmpAcc, tmpExp, swap, done) =>
  for(k, fun(i =>
    body(n^(k-i-1)*m, tmpAcc, tmpExp) ;
    if (i < k) { swap } else { done } ))))
  )
}

```

Listing 14: Extension of the acceptor translation

## VII. EVALUATION

We now want to evaluate our language-oriented compiler design. We will do this in two ways: 1) we will describe a qualitative comparison with the LIFT compiler highlighting the benefits of our approach over a compiler with similar design goals; 2) we perform an experimental evaluation to confirm that the code generated by the Shine compiler has the same runtime performance as code generated by LIFT.

### A. Qualitative comparison with LIFT

From the user perspective, the LIFT compiler and Shine have the same goal and RISE has almost the same interface as the LIFT IR. But their compiler design and implementations differ greatly.

Specifically, LIFT *does not* follow a language-oriented compiler design. It uses a single intermediate representation that lacks a formal type system. For example, LIFT lacks the concept of a function type despite primitives being modeled as functions. This makes specifying primitives cumbersome and the type inference implementation ad-hoc. Shine on the other hand, is implemented with two distinct languages that have designated purposes (optimizing vs. code generation). This more modular design comes with significant benefits for engineering, but also conceptually.

First, optimizing by rewriting is performed in a purely functional language without compromising the language design for other tasks. This is not the case in LIFT, where a single IR is used for both tasks and primitives are modelled not as functions, but as fully applied values, which makes the implementation of a rewrite system inconvenient.

Second, DPIA – the language for code generation – formalizes and enforces the necessary assumptions of code generation. This is not the case in LIFT where the compiler will fail with

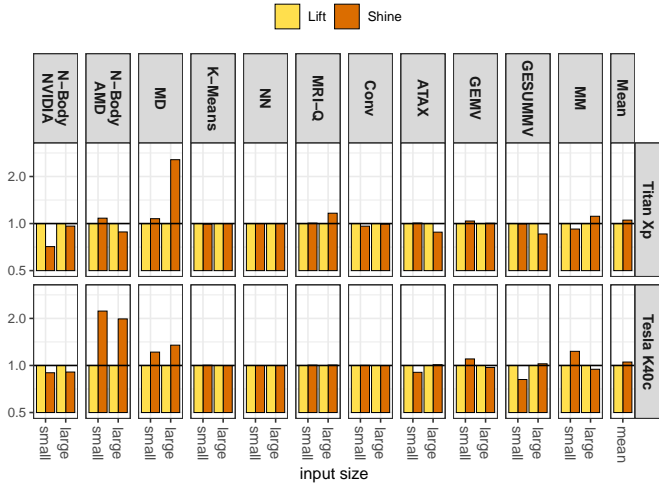


Fig. 5: Relative runtime performance of the code generated by Shine and LIFT. A higher bar indicates better performance.

internal errors or is forced to make ad-hoc implementation choices when these have not been encoded in the input program.

Finally, extensibility in LIFT is limited to functional primitives, whereas in Shine we can easily extend DPIA with imperative primitives that provide a safe interface re-usable for compiling many high-level primitives. The bottom up process of first establishing an imperative primitive in DPIA and then thinking about how to compile a functional primitive to it, provides a principled pathway to incorporate implementation patterns and library interfaces of the low-level target language.

### B. Runtime performance compared to LIFT

We now evaluate the quality of the code generated by Shine and LIFT using the benchmarks used in a previous LIFT paper [32]. We like to thank the authors for making their artifact publicly available. Figure 5 shows the runtime performance on two Nvidia GPUs. The benchmarks use the same optimizations in both compilers, even though LIFT makes some ad-hoc implementation choices, e.g., about memory allocation and vectorization, internally in the compiler rather than encoding them in the functional program as we do in Shine.

We expect that the generated code has the same performance for both compilers, as (mostly) the same optimizations are applied. For the mean across all benchmarks, this is indeed the case: the code generated by Shine is slightly faster (about 5%). There are two significant outliers, for which Shine generates significantly faster code: MD and N-Body AMD. Both benchmarks use vectorization and receive as input or produce as output arrays of `float4` values. While Shine honors this interface and generates OpenCL kernels with `float4` pointers, the LIFT compiler produces code with `float` pointers and uses `vload/vstore` vector instructions to load/store values from these arrays. In this case, this small code difference produces a significant performance gap. The NBody NVIDIA benchmark shows a clear performance benefit for the LIFT generated code. After inspection of the generated code, this can be explained

by the lack of a memory re-use mechanism in Shine, whereas the LIFT generated code uses less memory. Reusing memory is currently not modelled in the more formal DPIA, but could be added in the future.

To summarize, Shine shows the same performance as the LIFT compiler, while following a much better and more principled language-oriented compiler design.

## VIII. RELATED WORK

*Functional Compiler IRs:* We have extensively compared our work to the closest related work, LIFT [31, 32], throughout this paper. There exist several similar compilers with functional IRs, including Futhark [12], Accelerate [7], and Dex [21]. Delite [6] uses parallel patterns similar to RISE to provide a framework for building DSL compilers. Lücke et al. presents an implementation of a RISE-like language as a MLIR dialect [19]. The MLIR [16] dialect `linalg` cites LIFT as a direct influence. Of course there exist other IRs that incorporate functional aspects, such as the functional graph-based Thorin [17] IR that provides explicit support for higher-order functions. Many machine learning compilers, such as TensorFlow [1] and PyTorch [20], follow a functional graph-based IR that is inspired by ideas from data-flow programming.

*Extensible Compilers:* Rompf et al. present a technique based on staging for extensible compiler design [26]. Similarly, the Any DSL framework sees partial evaluation as the key to expressing compiler optimizations as easily extensible library code rather than internal IR transformations [18]. AnyDSL uses the functional Thorin IR mentioned above. Koehler and Steuwer argues for domain extensible compilers by extending the compiler with new image processing specific primitives and rewrite rules [14].

## IX. CONCLUSION

In this paper, we present the Shine compiler that follows a language-oriented compiler design. The compiler is composed of multiple formal programming languages that are used as intermediate representations.

Each language has a clear purpose, separating optimizing clearly from the code generation process. This simplifies both phases: optimizing is expressed exclusively by rewriting the higher-level functional RISE program encoding implementation and optimization choices; code generation bridges from the functional to the imperative paradigm and preserves the encoded implementation choices.

DPIA, the language for code generation, formalizes and checks the assumption that all implementation choices have been made before the code generation process starts.

By composing multiple languages, the compiler becomes easily extensible at various abstraction levels. We demonstrated extending with an imperative primitive that captures a desirable low-level double buffering code pattern.

Finally, our evaluation showed the benefits of our compiler design over the closely related LIFT compiler while maintaining the same runtime code performance.

## REFERENCES

- [1] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, Manjunath Kudlur, Josh Levenberg, Rajat Monga, Sherry Moore, Derek Gordon Murray, Benoit Steiner, Paul A. Tucker, Vijay Vasudevan, Pete Warden, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. Tensorflow: A system for large-scale machine learning. In *OSDI*, pages 265–283. USENIX Association, 2016.
- [2] Bowen Alpern, Mark N. Wegman, and F. Kenneth Zadeck. Detecting equality of variables in programs. In *POPL*, pages 1–11. ACM Press, 1988.
- [3] Andrew W. Appel. SSA is functional programming. *ACM SIGPLAN Notices*, 33(4):17–20, 1998.
- [4] Robert Atkey, Michel Steuwer, Sam Lindley, and Christophe Dubach. Strategy preserving compilation for parallel functional code. *CoRR*, abs/1710.08332, 2017.
- [5] Martin Bravenboer, Karl Trygve Kalleberg, Rob Vermaas, and Eelco Visser. Stratego/xt 0.17. A language and toolset for program transformation. *Sci. Comput. Program.*, 72(1-2):52–70, 2008.
- [6] Kevin J. Brown, HyoukJoong Lee, Tiark Rompf, Arvind K. Sujeeth, Christopher De Sa, Christopher R. Aberger, and Kunle Olukotun. Have abstraction and eat performance, too: optimized heterogeneous computing with parallel patterns. In *CGO*, pages 194–205. ACM, 2016.
- [7] Manuel M. T. Chakravarty, Gabriele Keller, Sean Lee, Trevor L. McDonell, and Vinod Grover. Accelerating haskell array codes with multicore gpus. In *DAMP*, pages 3–14. ACM, 2011.
- [8] Tianqi Chen, Thierry Moreau, Ziheng Jiang, Lianmin Zheng, Eddie Q. Yan, Haichen Shen, Meghan Cowan, Leyuan Wang, Yuwei Hu, Luis Ceze, Carlos Guestrin, and Arvind Krishnamurthy. TVM: an automated end-to-end optimizing compiler for deep learning. In *OSDI*, pages 578–594. USENIX Association, 2018.
- [9] Bastian Hagedorn, Larisa Stoltzfus, Michel Steuwer, Sergei Gorlatch, and Christophe Dubach. High performance stencil code generation with lift. In *CGO*, pages 100–112. ACM, 2018.
- [10] Bastian Hagedorn, Johannes Lenfers, Thomas Koehler, Xueying Qin, Sergei Gorlatch, and Michel Steuwer. Achieving high-performance the functional way: a functional pearl on expressing high-performance optimizations as rewrite strategies. *Proc. ACM Program. Lang.*, 4(ICFP):92:1–92:29, 2020.
- [11] John L. Hennessy and David A. Patterson. A new golden age for computer architecture. *Commun. ACM*, 62(2):48–60, 2019.
- [12] Troels Henriksen, Niels G. W. Serup, Martin Elsmann, Fritz Henglein, and Cosmin E. Oancea. Futhark: purely functional gpu-programming with nested parallelism and in-place array updates. In *PLDI*, pages 556–571. ACM, 2017.
- [13] Richard Kelsey. A correspondence between continuation passing style and static single assignment form. In *Intermediate Representations Workshop*, pages 13–23. ACM, 1995.
- [14] Thomas Koehler and Michel Steuwer. Towards a domain-extensible compiler: Optimizing an image processing pipeline on mobile cpus. In *CGO*, pages 27–38. IEEE, 2021.
- [15] Chris Lattner and Vikram S. Adve. LLVM: A compilation framework for lifelong program analysis & transformation. In *CGO*, pages 75–88. IEEE Computer Society, 2004.
- [16] Chris Lattner, Mehdi Amini, Uday Bondhugula, Albert Cohen, Andy Davis, Jacques A. Pienaar, River Riddle, Tatiana Shpeisman, Nicolas Vasilache, and Oleksandr Zinenko. MLIR: scaling compiler infrastructure for domain specific computation. In *CGO*, pages 2–14. IEEE, 2021.
- [17] Roland Leißa, Marcel Köster, and Sebastian Hack. A graph-based higher-order intermediate representation. In *CGO*, pages 202–212. IEEE Computer Society, 2015.
- [18] Roland Leißa, Klaas Boesche, Sebastian Hack, Arsène Pérard-Gayot, Richard Membarth, Philipp Slusallek, André Müller, and Bertil Schmidt. Anydsl: a partial evaluation framework for programming high-performance libraries. *Proc. ACM Program. Lang.*, 2(OOPSLA):119:1–119:30, 2018.
- [19] Martin Lücke, Michel Steuwer, and Aaron Smith. Integrating a functional pattern-based IR into MLIR. In *CC*, pages 12–22. ACM, 2021.
- [20] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. *CoRR*, abs/1912.01703, 2019.
- [21] Adam Paszke, Daniel Johnson, David Duvenaud, Dimitrios Vytiniotis, Alexey Radul, Matthew Johnson, Jonathan Ragan-Kelley, and Dougal Maclaurin. Getting to the point. index sets and parallelism-preserving autodiff for pointful array programming. *Proc. ACM Program. Lang.*, 5(ICFP), 2021.
- [22] Jonathan Ragan-Kelley, Connelly Barnes, Andrew Adams, Sylvain Paris, Frédo Durand, and Saman P. Amarasinghe. Halide: a language and compiler for optimizing parallelism, locality, and recomputation in image processing pipelines. In *PLDI*, pages 519–530. ACM, 2013.
- [23] Fabrice Rastello and Florent Bouchez Tichadou, editors. *SSA-based Compiler Design*. Springer, 2018.
- [24] Toomas Rimmelg, Thibaut Lutz, Michel Steuwer, and Christophe Dubach. Performance portable GPU code generation for matrix multiplication. In *GPGPU@PPoPP*, pages 22–31. ACM, 2016.
- [25] John C. Reynolds. *The Essence of Algol*, pages 67–88. Birkhäuser Boston, 1997.

- [26] Tiark Rompf, Arvind K. Sujeeth, Nada Amin, Kevin J. Brown, Vojin Jovanovic, HyoukJoong Lee, Manohar Jonnalagedda, Kunle Olukotun, and Martin Odersky. Optimizing data structures in high-level programs: new directions for extensible compilers based on staging. In *POPL*, pages 497–510. ACM, 2013.
- [27] Barry K. Rosen, Mark N. Wegman, and F. Kenneth Zadeck. Global value numbers and redundant computations. In *POPL*, pages 12–27. ACM Press, 1988.
- [28] Sven-Bodo Scholz. On programming scientific applications in SAC - A functional language extended by a subsystem for high-level array operations. In *Implementation of Functional Languages*, volume 1268 of *Lecture Notes in Computer Science*, pages 85–104. Springer, 1996.
- [29] Guy Lewis Steele. Lambda: The ultimate declarative. volume 379, 1976.
- [30] Guy Lewis Steele and Gerald Jay Sussman. Lambda: The ultimate imperative. volume 353, 1976.
- [31] Michel Steuwer, Christian Fensch, Sam Lindley, and Christophe Dubach. Generating performance portable code using rewrite rules: from high-level functional expressions to high-performance opencl code. In *ICFP*, pages 205–217. ACM, 2015.
- [32] Michel Steuwer, Toomas Remmelg, and Christophe Dubach. Lift: a functional data-parallel IR for high-performance GPU code generation. In *CGO*, pages 74–85. ACM, 2017.