MLIR: A Compiler Infrastructure for the End of Moore's Law

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Abstract

This work presents MLIR, a novel approach to building reusable and extensible compiler infrastructure. MLIR aims to address software fragmentation, improve compilation for heterogeneous hardware, significantly reduce the cost of building domain specific compilers, and aid in connecting existing compilers together. MLIR facilitates the design and implementation of code generators, translators and optimizers at different levels of abstraction and also across application domains, hardware targets and execution environments. The contribution of this work includes (1) discussion of MLIR as a research artifact, built for extension and evolution, and identifying the challenges and opportunities posed by this novel design point in design, semantics, optimization specification, system, and engineering. (2) evaluation of MLIR as a generalized infrastructure that reduces the cost of building compilers—describing diverse use-cases to show research and educational opportunities for future programming languages, compilers, execution environments, and computer architecture. The paper also presents the rationale for MLIR, its original design principles, structures and semantics.

1 Introduction

Compiler design is a mature field with a wide range of well-known algorithms, with applications to code generation, static analysis, program transformation, and more. The field also has seen the development of a number of mature technology platforms which have enabled massive reuse across the compiler community, including systems like the LLVM compiler infrastructure [25], the Java Virtual Machine (JVM) [26], and many others. A common characteristic of these popular systems is their "one size fits all" approach—a *single abstraction level* to interface with the system: the LLVM Intermediate Representation (IR) is roughly "C with vectors", and JVM provides an "object-oriented type system with a garbage collector" abstraction. This "one size fits all" approach is incredibly valuable—and in practice, the mapping to these domains from ubiquitous source languages (C/C++ and Java respectively) is straightforward.

At the same time, many problems are better modeled at a higher- or lower-level abstraction, e.g. source-level analysis of C++ code is very difficult on LLVM IR. We observe that many languages (including e.g. Swift, Rust, Julia, Fortran) develop their own IR in order to solve domain-specific problems, like language/library-specific optimizations, flow-sensitive type checking (e.g. for linear

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types), and to improve the implementation of the lowering process. Similarly, machine learning systems typically use "ML graphs" as a domain-specific abstraction in the same way.

While the development of domain specific IRs is a well studied art, their engineering and implementation cost remains high. The quality of the infrastructure is not always a first priority (or easy to justify) for implementers of these systems. Consequently, this can lead to lower quality compiler systems, including user-visible problems like slow compile times, buggy implementations, suboptimal diagnostic quality, poor debugging experience for optimized code, etc.

The MLIR project aims to directly tackle these programming language design and implementation challenges—by making it very cheap to define and introduce new abstraction levels, and provide "in the box" infrastructure to solve common compiler engineering problems. MLIR does this by (1) standardizing the Static Single Assignment (SSA)-based IR data structures, (2) providing a declarative system for defining *IR dialects*, and (3) providing a wide range of common infrastructure (including documentation, parsing and printing logic, location tracking, multithreaded compilation support, pass management, etc).

This paper explores various design points of the MLIR system, relates our experience applying it to a number of different problems, and discusses implications this work may have for language design and education.

1.1 Contributions

While most of the MLIR system is built out of well known compiler algorithms, the design points are sufficiently novel that it provides opportunities for interesting research. The contributions of this paper are:

- a description of a novel compiler infrastructure with important industrial and research applications;
- new approaches to building scalable and modular compiler systems;
- exploration of selected applications of MLIR to diverse domains, illustrating the generality of the system;
- shared experience developing systems that build on the MLIR infrastructure.

1.2 Where did MLIR come from?

Work on MLIR began with a realization that modern machine learning frameworks are composed of many different compilers, graph technologies, and runtime systems (see Figure 1)—which did not share a common infrastructure or design point, and not all of which were following best practices in compiler design. This manifested in multiple user-visible ways, including poor error messages, failures in edge cases, unpredictable performance, and difficulty generalizing the stack to support new hardware.

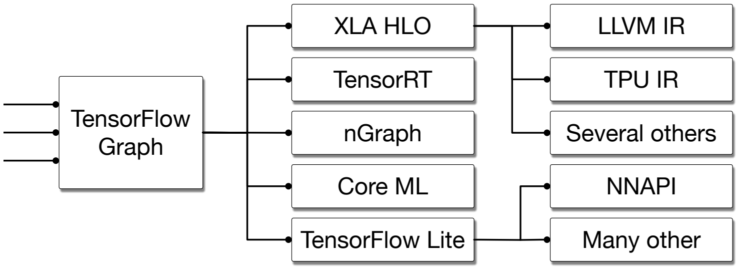


Figure 1: TensorFlow model execution spanning different frameworks.

We soon realized that the compiler industry as a whole has a similar problem: existing systems like LLVM are very successful at unifying and integrating work across a range of different language implementations, but modern high level languages often end up building their own high-level IR and reinventing a lot of the same kinds of technology for higher levels of abstraction (see Figure 2). At the same time, the LLVM community frequently struggled with questions about how to best represent parallel constructs, how to share implementation of common front-end lowering infrastructure (e.g. for C calling conventions, or cross-language features like OpenMP) with no satisfactory solutions being available.

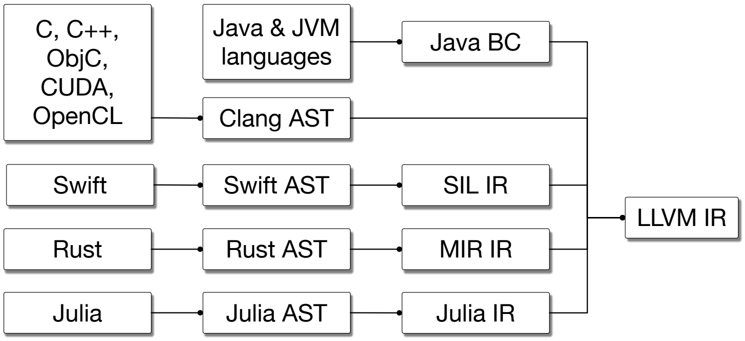


Figure 2: Compilation pipeline of different languages with multiple mid-level IRs for language-specific optimization with common backend for multiple hardware targets.

Faced with this challenge and perspective, we decided that we could not afford the engineering effort to implement N improved compiler instances, and we needed to build a more general solution. We reasoned that this would give us the ability to invest in one set of high quality infrastructure which would benefit multiple domains, would allow us to progressively upgrade existing systems in place, would make it easier for us to tackle pressing problems like heterogeneous compilation for specialized accelerators, and would provide interesting research opportunities to define and explore.

Now that we have a significant amount of experience building and deploying MLIR-based systems, we are able to look back on the rationale and design of the infrastructure, and discuss why this direction was pursued.

2 Design Principles

Let us now explore the requirements that guided the design of MLIR.

Little builtin, everything customizable The system is based on a minimal number of fundamental concepts, leaving most of the intermediate representation fully customizable. A handful of abstractions—types, operations and attributes, which are the most common in IRs—should be used to express everything else, allowing fewer and more consistent abstractions that are easy to comprehend, extend and adopt. Broadly, customizability ensures the system can adapt to changing requirements and is more likely to be applicable to future problems. In that sense, we ought to build an IR as a rich infrastructure with reusable components and programming abstractions supporting the syntax and semantics of its intermediate language.

A success criterion for customization is the possibility to express a diverse set of abstractions including machine learning graphs, ASTs, mathematical abstractions such as polyhedral, Control Flow Graphs (CFGs) and instruction-level IRs such as LLVM IR, all without hard coding concepts from these abstractions into the system.

Certainly, customizability creates a risk of internal fragmentation due to poorly compatible abstractions. While there is unlikely a purely technical solution to the ecosystem fragmentation problem, the system should encourage one to design reusable abstractions and assume they will be used outside of their initial scope.

SSA and regions The Static Single Assignment (SSA) form [15] is a widely used representation in compiler IRs. It provides numerous advantages including making dataflow analysis simple and sparse, is widely understood by the compiler community for its relation with continuation-passing style, and is established in major frameworks. While many existing IRs use a flat, linearized CFG, representing higher level abstractions push introducing *nested regions* as a first-class concept in the IR. This goes beyond the traditional region formation to lift higher level abstractions (e.g., loop trees), speeding up the compilation process or extracting instruction, or SIMD parallelism [22, 21, 37]. To support heterogeneous compilation, the system has to support the expression of structured control flow, concurrency constructs, closures in source languages, and many other purposes. One specific challenge is to make CFG-based analyses and transformations compose over nested regions.

In doing so, we aim to sacrifice the normalization, and sometimes the canonicalization properties of LLVM. Being able to lower a variety of data and control structures into a smaller collection of normalized representations is key to keeping compiler complexity under control. The canonical loop structure with its pre-header, header, latch, body, is a prototypical case of a linearized control flow representation of a variety of loop constructs in front-end languages. We aim at offering users a choice: depending on the compilation algorithm of interest, of the pass in the compilation flow, nested loops may be captured as nested regions, or as linearized control flow. By offering such a choice, we depart from the normalization-only orientation of LLVM while retaining the ability to deal with higher level abstractions when it matters. In turn, leveraging such choices raises questions about how to control the normalization of abstractions, whith is the purpose of the next paragraph.

Progressive lowering The system should support *progressive lowering*, i.e. from the higher-level representation down to the lowest-level, with the lowering being performed in small steps along multiple abstraction levels. The need for multiple levels of abstractions stems from the variety of platforms and programming models that a generic compiler infrastructure has to support.

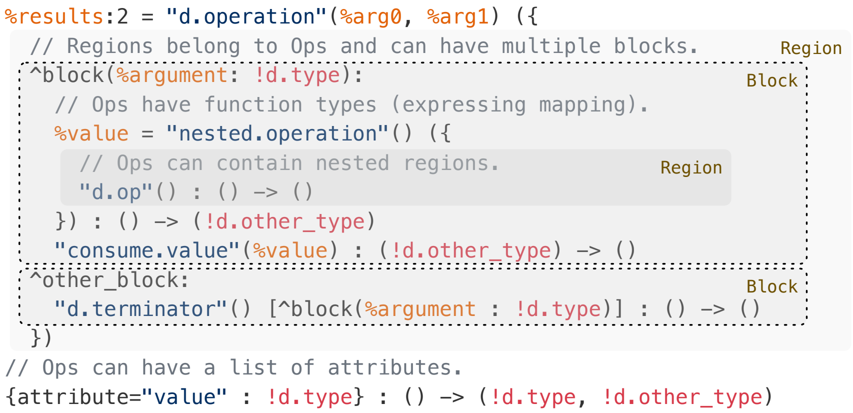
Previous compilers have been introducing multiple fixed levels of abstraction in their pipeline—e.g. the Open64 WHIRL representation [30] has five levels, as does the Clang compiler which lowers from ASTs to LLVM IR, to SelectionDAG, to MachineInstr, and to MCInst. Whereas these approaches are done in a rigid way, more flexible designs are required to support extensibility.

This has deep implications on the phase ordering of transformations. As compiler experts started implementing more and more transformation passes, complex interactions between these passes started appearing. It was shown early on that combining optimization passes allows the compiler to discover more facts about the program. One of the first illustrations of the benefits of combining passes was to mix constant propagation, value numbering and unreachable code elimination [13]. More generally, compiler passes can be roughly categorized into four roles: (1) optimizing transformations, (2) enabling transformations, (3) lowering and (4) cleanup. The system should allow for mixing and matching these roles at the granularity of a single operation rather than sequencing passes on the full compilation unit.

Maintain higher-level semantics The system needs to retain higher-level semantics and structure of computations that are required for analysis or optimizing performance. Attempts to raise semantics once lowered are fragile and shoehorning this information into a low-level often invasive (e.g., all passes need to be verified/revisited in the case of using debug information to record structure). Instead, the system should maintain structure of computation and progressively lower to the hardware abstraction. The loss of structure is then conscious and happens only where the structure is no longer needed to match the underlying execution model. For example, the system should preserve the structured control flow such as loop structure throughout the relevant transformations; removing this structure, i.e. going to CFG-based control flow, essentially means no further transformations will be performed on this level. The state of the art in modeling parallel computing constructs in a production compiler highlights how difficult the task may be in general [23, 42].

As a corollary, mixing different levels of abstractions and different concepts in the same IR is a key property of the system to allow a part of the representation to remain in higher-level abstraction while another part is lowered. This would enable, for instance, a compiler for a custom accelerator to reuse some higher-level structure and abstractions defined by the system alongside with primitive scalar/vector instructions specific to the accelerator.

IR validation The openness of the ecosystem calls for an extensive validation mechanism. While verification and testing are useful to detect compiler bugs, and to capture IR invariants, the need for robust validation methodologies and tools is amplified in an extensible system. The mechanism should aim to make this easy to define and as declarative as practical, providing a single source of truth.



```
%results:2 = "d.operation"(%arg0, %arg1) ({
 // Regions belong to Ops and can have multiple blocks.
 ^block(%argument: !d.type):
  // Ops have function types (expressing mapping).
  %value = "nested.operation"() ({
   // Ops can contain nested regions.
   "d.op"() : () -> ()
  }) : () -> (!d.other_type)
  "consume.value"(%value) : (!d.other_type) -> ()
 ^other_block:
  "d.terminator"() [^block(%argument : !d.type)] : () -> ()
 })
// Ops can have a list of attributes.
{attribute="value" : !d.type} : () -> (!d.type, !d.other_type)
```

Figure 3: Operation (Op) is a main entity in MLIR; operations contain a list of regions, regions contain a list of blocks, blocks contains a list of Ops, enabling recursive structures

A long term goal would be to reproduce the successes of translation validation [35, 29, 50, 51] and modern approaches to compiler testing [12]. Both are currently open problems in the context of an extensible compiler ecosystem.

Declarative rewrite patterns Defining representation modifiers should be as simple as that of new abstractions; a compiler infrastructure is only as good as the transformations it supports. Common transformations should be implementable as rewrite rules expressed declaratively, in a machine-analyzable format to reason about properties of the rewrites such as complexity and completion. Rewriting systems have been studied extensively for their soundness and efficiency, and applied to numerous compilation problems, from type systems to instruction selection. Since we aim for unprecedented extensibility and incremental lowering capabilities, this opens numerous avenues for modeling program transformations as rewrite systems. It also raises interesting questions about how to represent the rewrite rules and strategies, and how to build machine descriptions capable of steering rewriting strategies through multiple levels of abstraction. The system needs to address these questions while preserving extensibility and enforcing a sound, monotonic and reproducible behavior.

Source location tracking and traceability The provenance of an operation—including its original location and applied transformations—should be easily traceable within the system. This intends to address the lack-of-transparency problem, common to complex compilation systems, where it is virtually impossible to understand how the final representation was constructed from the original one.

This is particularly problematic when compiling safety-critical and sensitive applications, where tracing lowering and optimization steps is an essential component of software certification procedures [43]. When operating on secure code such as cryptographic protocols or algorithms operating on privacy-sensitive data, the compiler often faces seemingly redundant or cumbersome computations that embed a security or privacy property not fully captured by the functional semantics of the source program: this code may prevent the exposure of side channels or harden the code against cyber or fault attacks. Optimizations may alter or completely invalidate such protections [56]; this lack of transparency is known as WYSINWYX [6] in secure compilation. One indirect goal of accurately propagating high-level information to the lower levels is to help support secure and traceable compilation.

3 IR Design Details

This section describes the design of the IR in MLIR following the principles from the previous section.

```
// Attribute aliases can be forward-declared.
#map1 = (d0, d1) -> (d0 + d1)
#map3 = ()[s0] -> (s0)

// Ops may have regions attached.
"affine.for"(%arg0) ({
// Regions consist of a CFG of blocks with arguments.
^bb0(%arg4: index):
  // Block are lists of operations.
  "affine.for"(%arg0) ({
  ^bb0(%arg5: index):
    // Ops use and define typed values, which obey SSA.
    %0 = "affine.load"(%arg1, %arg4) {map = (d0) -> (d0)}
       : (memref<?xf32>, index) -> f32
    %1 = "affine.load"(%arg2, %arg5) {map = (d0) -> (d0)}
       : (memref<?xf32>, index) -> f32
    %2 = "std.mulf"(%0, %1) : (f32, f32) -> f32
    %3 = "affine.load"(%arg3, %arg4, %arg5) {map = #map1}
       : (memref<?xf32>, index, index) -> f32
    %4 = "std.addf"(%3, %2) : (f32, f32) -> f32
    "affine.store"(%4, %arg3, %arg4, %arg5) {map = #map1}
       : (f32, memref<?xf32>, index, index) -> ()
    // Blocks end with a terminator Op.
    "affine.terminator"() : () -> ()
  // Ops have a list of attributes.
  }) {lower_bound = () -> (0), step = 1 : index, upper_bound = #map3}
    : (index) -> ()
  "affine.terminator"() : () -> ()
}) {lower_bound = () -> (0), step = 1 : index, upper_bound = #map3}
  : (index) -> ()
```

Figure 4: MLIR *generic* representation for polynomial multiplication using affine and std dialects. The same IR is displayed with the custom syntax Figure 8.

Operations The unit of semantics in MLIR is an “operation”, referred to as *Op*. Everything from “instruction” to “function” to “module” are modeled as Ops in this system. MLIR does not have a fixed set of Ops, but allows (and encourages) user-defined extensions—compiler passes treat unknown Ops conservatively, and MLIR has rich support for describing the semantics of Ops to passes through traits, privileged operation hooks and optimization interfaces as described in Section 6.1.

Ops (see Figure 3) have a unique opcode, which, textually, is a string identifying its dialect and the operation. Ops take and produce zero or more *values*, called *operands* and *results* respectively, and these are maintained in SSA form. All values have a type, similarly to LLVM IR. In addition to an opcode, operands and results, Ops may also have *Attributes*, *Regions*, *Block Arguments*, and *Location Information* as well. Figure 4 illustrates values and Ops, `%`-identifiers are (packs of) named values, with “`:`” specifying the number in a pack if more than one and “#’ a particular value. In the generic textual representation, operation names are quoted string literals followed by operands in parentheses.

Attributes An MLIR attribute is structured compile-time static information, e.g., integer constant values, string data, or a list of constant floating point values. Attributes are typed, and each Op instance has an open key-value dictionary from string names to attribute values. In the generic syntax, attributes are between the Op operands and its type as a brace-enclosed comma-separated list of key-value pairs. For example, Figure 4 uses attributes to define bounds of a loop that are known to be constant affine forms: `{lower_bound = () -> (0), step = 1 : index, upper_bound = #map3}` where `lower_bound`, `upper_bound` and `step` are attribute names. The `() -> (0)` notation is used for inline affine forms, in this case producing an affine function producing a constant `0` value. The `#map3` notation is used for attribute *aliases*, which allow one to associate an attribute value with a label upfront and use the label anywhere an attribute value is expected.

As with opcodes, there is no fixed set of attributes. Attributes derive their meaning either from the Op semantics or from the dialect (Section 3) they are associated with. Attributes are also extensible, allowing direct references to foreign data structures, which is useful for integrating with existing systems. For example, an attribute may refer to the contents of (known at compile time) data storage in an ML system.

Location information MLIR provides a compact representation for *location information,* and encourages the processing and propagation of this information throughout the system. It can be used to keep the source program stack trace that produced an Op, to generate debug information. It standardizes the way to emit diagnostics from the compiler, and is used by a wide range of testing tools.

Location information is also extensible, allowing a compiler to refer to existing location tracking systems, high-level AST nodes, LLVM-style file-line-column address, DWARF debugging info or whatever else is needed for a high quality implementation.

Regions and blocks An instance of an Op may have a list of attached regions. A *region* provides the mechanism for nested structure in MLIR: a region contains a list of blocks, and a block contains a list of operations (which may contain regions). As with attributes, the semantics of a region are defined by the operation they are attached to, however the blocks inside the region (if more than one) form a Control Flow Graph (CFG). For example, the `affine.for` operation in Figure 4 is a loop with the single-block body attached as a region, located between `({` and `})` delimiters. The Op specifies the flow of control across regions. In this example, the body is executed repeatedly until the upper bound is reached.

The body of each region is a list of *blocks*, and each block ends with a *terminator* operation, that may have *successor* blocks to which the control flow may be transferred. Each terminator (e.g. “switch”, “conditional branch” or “unwind”) defines its own semantics. It may chose to transfer the control flow to another block in the same region, or return it to the Op enclosing the region. The graph of successors defines a CFG, allowing standard SSA-based control flow within a region.

Instead of using ϕ nodes, MLIR uses a functional form of SSA [2] where terminators pass values into *block arguments* defined by the successor block. Each block has a (potentially empty) list of typed block arguments, which are regular values and obey SSA. The semantics of terminator Ops defines what values the arguments of the block will take after the control is transferred. For the first (entry) block of the region, the values are defined by the semantics of the enclosing Op. For example, `affine.for` uses the entry block argument `%arg4` as loop induction variable.

Value dominance and visibility Ops can only use values that are in scope, i.e. *visible* according to SSA dominance, nesting, and semantic restrictions imposed by enclosing operations. Values are visible within a CFG if they obey standard SSA dominance relationships, where control is guaranteed to pass through a definition before reaching a use.

Region-based visibility is defined based on simple nesting of regions: if the operand to an Op is outside the current region, then it must be defined lexically above and outside the region of the use. This is what allows Ops within an `affine.for` operation to use values defined in outer scopes.

MLIR also allows operations to be defined as *isolated from above*, indicating that the operation is a scope barrier—e.g. the “std.func” Op defines a function, and it is not valid for operations within the function to refer to values defined outside the function. In addition to providing useful semantic checking, a module containing isolated-from-above Ops may be processed in parallel by an MLIR compiler since no use-def chains may cross the isolation barriers. This is a important for compilation to utilize multicore machines.

Symbols and symbol tables Ops can have a symbol table attached. This table is a standardized way of associating names, represented as strings, to IR objects, called *symbols*. The IR does not prescribe what symbols are used for, leaving it up to the Op definition. Symbols are most useful for named entities need not obey SSA: they cannot be redefined within the same table, but they can be used prior to their definition. For example, global variables, functions or named modules can be represented as symbols. Without this mechanism, it would have been impossible to define, e.g., recursive function referring to themselves in their definition. Symbol tables can be nested if an Op with a symbol table attached has associated regions containing similar Ops. MLIR provides a mechanism to reference symbols from an Op, including nested symbols.

Dialects MLIR manages extensibility using *Dialects*, which provide a logical grouping of Ops, attributes and types under a unique namespace. Dialects themselves do not introduce any new semantics but serve as a logical grouping mechanism and can be used to provide dialect generic Op support (e.g., constant folding behavior for all ops in the dialect). The dialect namespace appears as a dot-separated prefix in the opcode, e.g., Figure 4 uses `affine` and `std` dialects.

The separation of Ops, types and attributes into dialects is conceptual and is akin to designing a set of modular libraries. For example, a dialect can contain Ops and types for operating on hardware vectors (e.g., shuffle, insert/extract element, mask), and another dialect can contain Ops and types for operating on algebraic vectors (e.g. absolute value, dot product, etc.). Whether both dialects use the same vector type and where does this type belong are design decisions left to the user of MLIR.

While it is possible to put all Ops, types and attributes in a single dialect, it would quickly become unmanageable due to the large number of simultaneously present concepts and name conflicts, amongst other issues. Although each Op, type and attribute belongs to exactly one dialect, MLIR explicitly supports a mix of dialects to enable progressive lowering. Ops from different dialects can coexist at any level of the IR at any time, they can use types defined in different dialects, etc. Intermixing of dialects allows for greater reuse, extensibility and provides flexibility that otherwise would require developers to resort to all kinds of non-composable workarounds.

Type system Each value in MLIR has a type, which is specified in the Op that produces the value or in the block that defines the value as an argument. Types provide compile-time semantics for the IR. The type system in MLIR is user-extensible, and may refer to existing foreign type systems (e.g. an `llvm::Type` or a `clang::Type`). MLIR enforces strict type equality checking and does not provide type conversion rules. Ops list their inputs and result types using trailing function-like syntax. In Figure 4, `std.load` maps from the memory reference and index types to the type of the value it loads.

From the type theory point of view, MLIR only supports non-dependent types, including trivial, parametric, function, sum and product types. While it is possible to implement a dependent type system by combining Ops with symbols and user-defined types in a literal interpretation of Curry-Howard isomorphism, such types will be opaque to the IR.

Standard types In addition, MLIR provides a standardized set of commonly used types, including arbitrary precision integers, standard floating point types, and simple common containers—tuples, multi-dimensional vectors, and tensors. These types are merely a convenience that are useful to authors of dialects, but their use is not required.

Functions and modules Similarly to conventional IRs, MLIR is usually structured into functions and modules. However, these are not new or separate concepts in MLIR: they are implemented as Ops in the builtin dialect.

A module is an Op with a single region containing a single block, and terminated by a dummy Op that does not transfer the control flow. A module defines a symbol and can be referenced. Like any block, its body contains a list of Ops, which may be functions, global variables, compiler metadata, or other top-level constructs.

A function is an Op with a single region, with arguments corresponding to function arguments. It defines a symbol and can be referenced by name. The control flow is transferred into a function using a function call Op. Once inside, the control flow follows the CFG of the blocks in the region. A "return" terminator does not have successors and instead terminates the region execution, transferring the control flow back to the call-site of the function. Any operands of the "return" terminator Op are the returned values of the function.

4 IR Infrastructure

Beyond the IR itself, MLIR provides infrastructure for defining IR elements such as dialects, Ops, pattern rewrites, verification and reusable passes. The infrastructure aspect of MLIR is essential for providing extensibility and ease of use when defining new abstractions and using MLIR as an optimization toolkit.

```
// An Op is a TableGen definition that inherits the "Op" class parameterized
// with the Op name
def LeakyReluOp: Op<"leaky_relu",
    // and a list of traits used for verification and optimization.
    [NoSideEffect, SameOperandsAndResultType]> {
  // The body of the definition contains named fields for a one-line
  // documentation summary for the Op.
  let summary = "Leaky Relu operator";

  // The Op can also a full-text description that can be used to generate
  // documentation for the dialect.
  let description = [{
    Element-wise Leaky ReLU operator
      x -> x >= 0 ? x : (alpha * x)
  }];

  // Op can have a list of named arguments, which include typed operands
  // and attributes.
  let arguments = (ins AnyTensor:$input, F32Attr:$alpha);

  // And a list of named and typed outputs.
  let results = (outs AnyTensor:$output);
}
```

Figure 5: Operation Definition Syntax (ODS) provides a concise way of defining new Ops in MLIR. Here, one defines the `LeakyRelu` Op taking a tensor and a floating-point value, and returning a tensor of the same type as the input one.

4.1 Operation description

MLIR uses TableGen-based [47] specification for Operation Descriptions (ODS), defining the structure of an Op and components of its verifier declaratively. TableGen is a data modeling tool intended to help define and maintain records of domain-specific information, used extensively in LLVM. We chose it for modeling Ops and rewrite patterns to leverage its acceptance by the industry. ODS can be seen as a DSL for MLIR Op definition *embedded* into the TableGen input language, so the ODS syntax is imposed by TableGen, but the MLIR-specific semantics is provided by ODS. The ODS definition is ultimately translated into C++ code (including Op classes with named accessors, verification, etc.) which interoperate with the rest of the system.

Ops are modeled in ODS using the TableGen `Op` class. Figure 5 shows an example of Op ODS definition. Each defined Op has a *name* which is a unique identifier, a list of *traits* that describe Op properties, a list of *arguments* that specify Op's operands and attributes, and a list of Op's *results*. Arguments and results have names and type constraints (e.g., fixed-shape tensor of `float` or `int32`). Op definition may also specify human readable Op description for the documentation. And a (limited) custom textual form for which custom printer/parser will be generated. When Op definition requires finer-grain control than ODS provides, additional C++ code can be injected via *builder*, *printer*, *parser*, *verifier* clauses. Op traits can be generic, e.g., "has no side-effects", and dialect- or ODS-specific, e.g., "has custom exporter". Traits in ODS may be backed by C++ classes defining the behavior of the trait. There is no fixed set of traits, but some traits are known by ODS (e.g., "shape result and operand type" represents a constraint that fully captures the output type given input types) or optimizers (e.g., "has no side-effects", see Section 6.1).

Type constraints check properties of the type of arguments/results and are user/dialect extensible. MLIR infrastructure also provides numerous pre-defined type constraints, such as "any type", "tensor with element satisfying the given constraint", "vector of given rank", etc. ODS also has limited support for automatically deducing the return type of results of operands using the constraints induced by the traits, see Section 4.2 for more information.

4.2 Declarative rewrites

Many MLIR transformations involve Op manipulations, and while some transformations require complex modifications of the IR, many others can be expressed as simple rewrites on the DAG

```
// A rewrite pattern declaring an equivalence between a source and target DAG.
def : Pattern<
    // The first parameter is the source DAG with nodes corresponding to Ops in
    // ODS followed by a list of named arguments, potentially with more type
    // constraints.
    (LeakyReluOp $arg, F32Attr:$alpha),

    // The second parameter is a list of DAGs that is used to replace matched
    // source DAG. DRR supports multiple result patterns as well as auxiliary
    // Ops, which are used for building the replacement ops but are not
    // directly used for replacements. The DAGs may refer to matched values in
    // the source DAG or those created in target.
    [(SelectOp (CmpFOp CMPF_P_ODT
      // A referenced argument bound in the source DAG.
        $arg
      // Nested DAG construct Ops that produce value from attribute created in
      // pattern.
        (ConstantOp ConstantAttr<F32Attr, "0.">))
      // And the two final, required arguments of SelectOp.
        $arg,  (ConstantOp $alpha))]>;
```

Figure 6: Declarative graph rewrite rule transforming a LeakyRelu into a Compare-Float, followed by a Select.

defined by SSA use-def relations. MLIR provides a graph rewriting framework complemented with the Declarative Rewrite Rule (DRR) system that makes it simple to express patterns.

Similarly to ODS, DRR is a DSL embedded into the TableGen language. DRR expresses source and target DAG patterns along with constraints (including dynamic constraints [49]) and benefits for pattern prioritization. Patterns can capture and reuse arguments of an Op. Conceptually, DRR expresses equivalence of DAGs under specific constraints. Figure 6 gives an example of a DRR pattern that converts an Op defined in Figure 5 into common lower-level implementation consisting of a `compare` and a `select`.

DRR is converted into C++ code, which can be intermixed with more complex patterns defined directly in C++ using the generic graph rewriting framework. This ability allows MLIR to keep the common case simple without restricting generality of the framework.

4.3 Pass manager

The MLIR pass manager organizes and handles the efficient execution of a series of *IR passes* operating on various granularities. Whereas pass management in existing systems is typically defined over a fixed granularity (e.g., module, function or loop pass managers), in MLIR modules and functions are not special—they are merely Ops with regions and there can be multiple variants of them. Therefore, the MLIR pass manager is also not specialized on a fixed set of ops, but instead works on arbitrary Ops at arbitrary levels of nesting.

Parallel compilation An important requirement of MLIR is the need to utilize multi-core machines for faster compilation. The pass manager supports concurrent traversal and modification of the intermediate representation, which is made possible by invariants provided by “isolated-from-above” property of operations, because the SSA use-def chains cannot cross the region boundaries of these ops. Operations with this behavior (e.g. the “std.func” operation) thus define a tree of regions that may be processed in parallel.

This requirement is the reason why (in contrast to, for example, LLVM), MLIR does not feature whole-module use-def chains. Global objects are referenced through symbol table entries, and constants are implemented as operations with associated attributes.

4.4 Round-trippable textual IR form

The IR and Ops in MLIR have a textual representation that fully reflects the in-memory representation, which is critical for debugging, understanding the IR during transformations, and for writing test cases. The raw IR form shown in Figure 4 is verbose and difficult to understand. Therefore MLIR allows for defining custom printing and parsing formats for Ops, which allows the example to be printed and parsed as shown in Figure 8, which is much easier to work with.

Both forms are fully round-trippable and each compiler pass may be tested separately, using the textual form as both input and output. Since there is no hidden state, the result of running an individual pass is identical to running the same pass in the full pass pipeline. This approach is user-friendly, as the IR form can be created by hand, and IR transformations are easy to trace.

4.5 Documentation

Dialects, Ops and Interfaces have a documentation generated from their ODS descriptions. Beyond one line *summary* and more readable *description*, the generated documentation includes argument and result type constraints. As the same source is used for both the verification code and documentation, the documentation has higher changes of remaining in sync with runtime behavior.

4.6 Verifiers

Verifiers are used to enforce structural correctness of the IR and invariants of Ops, allowing passes to assume a verified IR with invariants checked, and also serves as a debugging tool. Verification starts with checking structural properties of MLIR overall: types must match exactly, values are defined only once and obey dominance and visibility, symbol names are unique in the symbol table, all blocks end with terminator Ops, etc. After that, individual Op and attribute verifiers are applied. Each Op may define a set of structural and semantic rules that check its validity. For example, a binary Op checks that it has two operands, many Ops only accept values of specific types, and many require specific attributes or regions attached. Similarly, dialect attributes can be only allowed on specific Ops or impose further restrictions on the Ops to which they are attached. For example, a dialect attribute can require an Op to only use types defined in the dialect even though the Op itself is more generic. Verification failures are considered invariant violations and abort compilation.

5 Evaluation: Applications of MLIR

MLIR is a system that aims to generalize and drive a wide range of compiler projects, so our primary evaluation metric is to show that it is being adopted and used for diverse projects. We provide a summary of community activity and describe a few use cases in more detail to highlight the generality and extensibility of MLIR and demonstrate how well it implements the customizability design principle.

Today, MLIR is a growing open source project with a community spanning academia and industry. For example, the academic workshop about use of MLIR in High-Performance Computing (HPC) was attended by individuals from 16 universities and involved 4 national laboratories from 4 different countries. MLIR was also endorsed by 14 multinational companies and at the LLVM Developer Meeting more than 100 industry developers attended a roundtable event about MLIR. Community adoption and participation is a proxy measure for usability and need. More than 26 dialects are in development in public or private and 7 projects across different companies are replacing custom infrastructure with MLIR. We argue that this shows a real need for MLIR, as well as endorses its usability.

5.1 TensorFlow graphs

While the other discussed representations are familiar to most compiler developments, one of key use cases for MLIR is to support the development of machine learning frameworks. Their internal representations is often based on a data flow graph [53] with a dynamic execution semantics.

TensorFlow [1] is an example of such framework. Its representation is a high-level dataflow computation where the nodes are computations which can be placed on various devices, including specific hardware accelerators.

MLIR is used in TensorFlow to model this internal representation and perform transformations for the use cases presented in Figure 1: from simple algebraic optimizations to retargeting graphs for

```
%0 = tf.graph (%arg0 : tensor<f32>, %arg1 : tensor<f32>,
               %arg2 : !tf.resource) {
  // Execution of these operations is asynchronous, the %control return value
  // can be used to impose extra runtime ordering, for example the assignment
  // to the variable %arg2 is ordered after the read explicitly below.
  %1, %control = tf.ReadVariableOp(%arg2)
     : (!tf.resource) -> (tensor<f32>, !tf.control)
  %2, %control_1 = tf.Add(%arg0, %1)
     : (tensor<f32>, tensor<f32>) -> (tensor<f32>, !tf.control)
  %control_2 = tf.AssignVariableOp(%arg2, %arg0, %control)
     : (!tf.resource, tensor<f32>) -> !tf.control
  %3, %control_3 = tf.Add(%2, %arg1)
     : (tensor<f32>, tensor<f32>) -> (tensor<f32>, !tf.control)
  tf.fetch %3, %control_2 : tensor<f32>, !tf.control
}
```

Figure 7: SSA representation of a TensorFlow dataflow graph in MLIR.

parallel execution on data center clusters of hardware accelerators, from lowering to a representation suitable for mobile deployment to generating efficient native code using tools like XLA [57]. The representation of a TensorFlow graph in MLIR is illustrated on Figure 7.

5.2 Polyhedral code generation

One of the original motivations for MLIR was the exploration of polyhedral code generation for accelerators. The affine dialect is a simplified polyhedral representation that was designed to enable progressive lowering. While a full exploration of the design points here is out of scope for this paper, we illustrate aspects of the affine dialect to show the modeling power of MLIR and contrast the affine dialect with past representations [17, 19, 54, 55, 52].

5.2.1 Similarities

The MLIR affine dialect operates on a structured multi-dimensional type for all accesses to memory. In the default case, these structured types are *injective*: different indexings are guaranteed not to alias by construction, a common precondition for polyhedral dependence analyses.

Affine modeling is split in two parts. Attributes are used to model affine maps and integer sets at compile-time and Ops are used to apply affine restrictions to the code. Namely, `affine.for` Op is a “for” loop with bounds expressed as affine maps of values required to be invariant in a function. Thus loops have static control flow. Similarly, `affine.if` is a conditional restricted by affine integer sets. The bodies of loops and conditionals are regions that use `affine.load` and `affine.store` to restrict indexing to affine forms of surrounding loop iterators. This enables exact affine dependence analysis while avoiding the need to infer affine forms from a lossy lower-level representation.

5.2.2 Differences

The differences with existing polyhedral frameworks are numerous, we can characterize them in four categories:

(1) *Rich types*: the MLIR structured memory reference type contains a layout map connecting the index space of the buffer to the actual address space. This separation of concerns makes loop and data transformations compose better: changes to data layout do not affect the code and do not pollute dependence analysis. Such mixes of transformations have been explored previously [38] but are uncommon.

(2) *Mix of abstractions*: Bodies of affine loops in MLIR can be expressed with operations on typed SSA values. Therefore, all traditional compiler analyses and transformations remain applicable and can be interleaved with polyhedral transformations. On the contrary, polyhedral compilers often abstract such details away completely, making it challenging for a polyhedral compiler to manipulate, e.g., vector types.

```
// Affine loops are Ops with regions.
affine.for %arg0 = 0 to %N {
  // Only loop-invariant values, loop iterators, and affine functions of
  // those are allowed.
  affine.for %arg1 = 0 to %N {
    // Body of affine for loops obey SSA.
    %0 = affine.load %A[%arg0] : memref<? x f32>
    // Structured memory reference (memref) type can have
    // affine layout maps.
    %1 = affine.load %B[%arg1] : memref<? x f32, (d0)[s0] -> (d0 + s0)>
    %2 = mulf %0, %1 : f32
    // Affine load/store can have affine expressions as subscripts.
    %3 = affine.load %C[%arg0 + %arg1] : memref<? x f32>
    %4 = addf %3, %2 : f32
    affine.store %4, %C[%arg0 + %arg1] : memref<? x f32>
  }
}
```

Figure 8: Representing polynomial multiplication kernel `C(i+j) += A(i) * B(j)` using MLIR affine dialect.

(3) *Smaller representation gap*: One of the key features of the polyhedral model is its ability to represent the order of loop iterations in the *type system*. In this system, a large number of loop transformations compose directly and can be reasoned about using simple mathematical abstractions [19]. However, polyhedral transformations require *raising* into a representation often drastically different from the original [20, 10]. Furthermore, the conversion from transformed polyhedra to loops is computationally hard [7]. MLIR-based representation maintains high-level loop structure around lower-level representation, removing the need for raising.

(4) Compilation speed is a crucial goal for MLIR as discussed in Section 4.3, but has not been a focus of most existing polyhedral approaches. These rely heavily on algorithms with exponential complexity: on integer linear programming to derive loop orderings automatically and on polyhedron scanning algorithms to convert the representation back to loops. The approach taken by MLIR explicitly does not rely on polyhedron scanning since loops are preserved in the IR.

Experience with the affine dialect shows that it is useful for a wide range of code generation projects, and its development was important exploration that the MLIR design made practical.

5.3 Fortran IR (FIR)

The LLVM Fortran frontend “flang” is currently under major development, led by NVIDIA/PGI. Similar to Swift, Rust, and others, flang needs a specialized IR in order to support advanced transformations for high-performance Fortran codebase, and is using MLIR to support these Fortran-specific optimizations [44]. These high-level optimizations—advanced loop optimizations, array copy elimination, call specialization, devirtualization—would be hard implement using only LLVM.

For example, FIR is able to model Fortran virtual dispatch table as a first class concept (see Figure 9).

```
// Dispatch table for type(u)
fir.dispatch_table @dtable_type_u {
  fir.dt_entry "method", @u_method
}

func @some_func() {
  %uv = fir.alloca !fir.type<u> : !fir.ref<!fir.type<u>>
  fir.dispatch "method"(%uv) : (!fir.ref<!fir.type<u>>) -> ()
  // ...
}
```

Figure 9: FIR has first class support for dynamic virtual function dispatch table.

The ability to model the high-level semantics of the programming language in a structured IR is very powerful. For example, first-class modeling of the dispatch tables allows a robust devirtualization pass to be implemented. While this could have been implemented with a bespoke compiler IR, the use of MLIR allowed the flang developers to spend their engineering resources focused on the IR design for their domain instead of reimplementing basic infrastructure.

The choice of MLIR also unlocks the reusability of other dialects that are not specific to Fortran: a language-independent OpenMP dialect could be shared between Fortran and C language frontends. Similarly, targeting a heterogeneous platform using OpenACC becomes tractable within MLIR through the sharing and reuse of the GPU-oriented dialects and passes. This is straightforward thanks to MLIR begin specifically designed to support a mix of composable dialects.

5.4 Domain-specific compilers

The applications of MLIR above are within large compilation workflows, but it is also used to build domain specific compilers for specific small workflows. A reusable and modular infrastructure makes these specialized paths feasible and relatively cheap to build.

Optimizing MLIR pattern rewriting MLIR has an extensible system for pattern rewrites described in Section 4. In addition to statically declared patterns, we had applications where the rewrite patterns needed to be dynamically extensible at runtime, allowing hardware vendors to add new lowerings in drivers. The solution was to express MLIR pattern rewrites as an MLIR dialect itself, allowing us to use MLIR infrastructure to build and optimize efficient Finite State Machine (FSM) matcher and rewriters on the fly. This work includes FSM optimizations seen in other systems, such as the LLVM SelectionDAG and GlobalISel instruction selection systems.

Lattice regression compiler Lattice regression [18] is a machine learning technique renowned for fast evaluation times and interpretability. The predecessor of the compiler was implemented using C++ templates. This allowed for high-performance code with metaprogramming, but expressing general optimizations on the end-to-end models was not straightforward. This particular lattice regression system is used in applications with multiple millions of users and hence performance improvements are critical.

MLIR was used as the basis for a new compiler for this specialized area, which was driven by a specialized search approach—effectively resulting in a machine learning problem being solved during compilation. The resultant compiler was developed by investing a 3 person-month effort, and resulted in up to $8\times$ performance improvement on a production model, while also improving transparency during compilation.

6 Consequences of the MLIR Design

The MLIR design facilitates the modeling of new language and compilation abstractions while reusing existing, generic ones as well as their associated compilation methods. Effectively, the solution to many problems is to “add new ops, new types”, possibly collected into “a new dialect”. This is a significant design shift for compiler engineering. It produces new opportunities, challenges, and insights. This section explores a few of them.

6.1 Reusable compiler passes

The ability to represent multiple levels of abstraction in one IR creates the natural desire to write passes that work across multiple levels of abstraction. A common question about MLIR is “how do you write a compiler pass when you have openly extensible operations and type system?” While it is always possible for a compiler pass to treat unknown constructs in a conservatively correct way, our goal is to produce high performance code, so we need to do useful things in common cases. We have found four major approaches:

Fundamental operation traits Some “bread and butter” compiler passes like Dead Code Elimination and Common Subexpression Elimination rely on very simple properties (like “has no side effect” or “is commutative”) that we define as Op traits. The definition of an operation in ODS allows the author of the operation to specify these traits, and passes can uses this information to remain applicable across many different abstraction domains.

MLIR is extensible enough that it has a few structural properties, including information about whether an operation is known to be a control flow terminator, whether an operation containing a region is known to be isolated-from-above, etc. These allow generic modeling and processing of functions, closures, modules, and other code structures.

Privileged operation hooks While certain traits can be modeled with a single bit, others need C++ code to provide an implementation—constant folding logic for example. MLIR has first class support for certain hooks applicable to a large number of passes. These hooks can either be implemented on a per-operation basis, or in the Dialect object itself. The later approach is convenient for things like constant folding of TensorFlow ops, where delegation to existing logic is straightforward.

While constant folding is very important functionality, a more interesting hook is `getCanonicalizationPatterns`, which allows one to specify folding patterns that apply to an operation. This enables open extensibility of important algebraic simplifications (e.g. $x - x \to 0$, $\min(x, y, y) \to \min(x, y)$ etc.) and powers a common "Canonicalization" pass that can now be applied to all dialects. This allows this single extensible system to subsume things like "InstCombine", "DAGCombine", "PeepholeOptimizer", "SILCombine", and other special purpose passes seen in the LLVM ecosystem (and other compilers), which are a well-known maintenance and complexity burden.

Optimization interfaces A primary goal of MLIR is to allow open extensibility—not just in terms of operations and types, but also in terms of transformations. While canonicalization and constant folding are critical operations, there are a number of standard transformations that need to be parameterized in certain ways—e.g., to describe transformation specific properties, to implement cost models, etc.

The solution is a subsystem known as "Optimization Interfaces". Consider the MLIR inlining pass: we would like the inliner to work on TensorFlow graphs, Flang functions, closures in a functional language etc.—but the inliner does not know what call sites or even the callees are! The core characteristics that an inliner needs to know are:

- whether it is valid to inline an operation into a given region;
- how to handle terminator operations that ended up in the middle of a block after inlining.

```
struct DialectInlinerInterface {
  /// Returns true if the given operation 'op', that is registered to this
  /// dialect, can be inlined into the given region, false otherwise.
  bool isLegalToInline(Operation *, Region *, BlockAndValueMapping &) const;

  /// Handle the given inlined terminator by replacing it with a new operation
  /// as necessary.
  void handleTerminator(Operation *, ArrayRef<Value *> ) const;
};
```

Figure 10: Dialect interface to query legality of inlining.

In order to know these properties, the Inliner pass defines the interface in Figure 10. Individual operations and dialects may register their implementation of this interface with MLIR to benefit from the generic inliner pass. If an operation or dialect fails to provide an interface then the corresponding optimization pass will treat the operation conservatively. This design allows the implementer of a dialect to get up and running quickly, but derive more value out of the system by putting more implementation effort into interfaces likes these over time.

Optimization interfaces also provide modularity benefit for the core compiler, because the dialect specific logic is implemented within the dialects themselves, instead of inside the core transformations.

Dialect specific passes Finally, it is valid and useful to define passes that are specific to particular dialects, which can be driven by full semantics of operations in the dialect(s) they are designed for. These passes are just as useful in the MLIR system as they are in other compiler systems. For example, code generators that want to do custom scheduling of machine instructions based on particular machine constraints or other tricks that do not fit into a broader framework. This is a simple and useful starting point for new transformations, where generalization isn't required.

6.2 Mixing dialects together

One of the most profound (but also most difficult to grok) aspects of MLIR is that it allows and encourages mixing operations from different dialects together into a single program. While certain cases of this are reasonably easy to understand (e.g. holding host and accelerator computation in the same module) the most interesting cases occur when dialects are directly mixed— because this enables an entire class of reuse that we have not seen in other systems.

Consider the affine dialect described in Section 5.2. The definition of affine control flow and affine mappings are independent of the semantics of the operations that are contained in affine regions. In our case, we combine the affine dialect with the "standard" dialect that represents simple arithmetic in a target independent form like LLVM IR, with multiple target-specific machine instruction dialects for internal accelerators. Others have combined it with abstractions from other problem domains.

The ability to reuse generic polyhedral transformations (using Op interfaces to get semantics of operations in specific transformations) is a powerful (and exciting to us) way of factoring compiler infrastructure. Another example is that an OpenMP dialect could be used and reused across a wide variety of source-language IRs.

6.3 Interoperability

Our work involves interoperation with a large number of existing systems, e.g., machine learning graphs encoded as protocol buffers, compiler IRs including LLVM IR, proprietary instruction sets, etc. Often the representation has a number of suboptimal or unfortunate decisions that made sense in the context of an existing system, but capabilities of MLIR enable a more expressive representation. Because importers and exporters are notoriously difficult to test (often the test cases are binary formats), we want to make sure their complexity is minimized.

The solution is to define a dialect that corresponds to the foreign system as directly as possible— allowing round tripping to-and-from that format in a simple and predictable way. Once the IR is imported into MLIR form, it can be raised and lowered to a more convenient IR using all of the MLIR infrastructure for doing these transformations, and allows those transformations to be tested similarly to all the other MLIR passes are.

There are numerous examples of such dialects, including: a) the LLVM dialect—which maps LLVM IR into MLIR, b) the representation of TensorFlow graphs—which is raised to ease analysis and transformations related to "switch and merge" nodes in TensorFlow, and c) functional-style control flow operators—"functional while" and "functional if" are common in machine learning graphs, in which it is more convenient to work with their bodies as regions instead of out-of-line functions.

This approach has worked well for us, and the MLIR tooling has also been useful to write tests for these foreign binary file formats.

6.4 Unopinionated design provides new challenges

While MLIR allows one to define almost arbitrary abstractions, it provides very little guidance on what *should* be done: what works better or worse in practice? We now have some experience with a number of engineers and researchers applying the techniques and technologies to new problem domains, and have realized that the "art" of compiler IR design and abstraction design is not well understood in the compiler and languages field—many people work within the constraints of established systems, but relatively few have had the opportunity define the abstractions themselves.

This is a challenge, but is also another set of opportunities for future research. The broader MLIR community is building a significant amount of expertise with these abstraction design trade-offs, and we expect this to be a fertile area of study over time.

6.5 Looking forward

The design of MLIR is different enough from other compiler infrastructures that we are still learning—even after building and applying it to many different systems. We believe that there is still a lot to discover, and several more years of research will be required until the design points are all fully understood and best practices are established. For example, the rise of out-of-tree dialects, increasing number of source language frontends using MLIR, possible application to Abstract Syntax Trees, and applications to structured data (like JSON, protocol buffers, etc) which are still very early and are likely to uncover interesting new challenges and opportunities.

7 Related Work

MLIR is a project that overlaps with multiple different domains. While the composed infrastructure provides a novel system, individual components have analogs in the literature. For references and discussion directly related to the IR design itself, please refer to Section 2.

MLIR is a compiler infrastructure akin to LLVM [25], but where LLVM has been a great boon to scalar optimizations and homogeneous compilation, MLIR aims to model a rich set of data structures and algorithms as first-class values and operations, including tensor algebra and algorithms, graph representations, as well as heterogeneous compilation. MLIR allows mix-and-match optimization decomposing compilation passes into components and redefining lowering, cleanup roles. This is largely attributed to the pattern rewriting infrastructure, capturing full-fledged transformations as a composition of small local patterns and controlling which pattern rewrites are applied at the granularity of an individual operation. Extending, formalizing, and verifying the rewriting logic automatically would be an important next step [9, 27]. On the backend side, MLIR's DDR has an analogue to LLVM's instruction selection infrastructure, supporting extensible operations with multi-result patterns and specification as constraints [49].

Numerous programming languages and models tackle hardware heterogeneity. Originally a homogeneous programming model, OpenMP added support for offloading tasks and parallel regions to accelerators [32], based on earlier proposals such as StarSs and OpenACC [34, 31]. C++ AMP, HCC and SyCL leverage a conventional Clang/LLVM flow and modern C++ to provide a high-level abstraction for hardware acceleration [46]. Unfortunately, all these examples very quickly lower high-level constructs to calls to a runtime execution environment, relying on pre-existing optimizations in the host language (typically C++) to alleviate the abstraction penalty. Far fewer efforts target the heterogeneous compilation process itself. Parallel intermediate representations extending LLVM IR address part of the issue but traditionally focus on the homogeneous setting [23, 42]. The most ambitious effort to date may be Liquid Metal [3], with a co-designed Domain Specific Language (DSL) and compilation flow converting managed object semantics into static, vector or reconfigurable hardware; yet most of the effort in its Lime compiler reside in fitting round objects into square hardware (paraphrasing Kou and Palsberg [24]). MLIR provides a direct embedding for high level languages embracing heterogeneity through extensible set of operations and types, while providing a common infrastructure for gradually lowering these constructs with maximal reuse of common components across the different targets.

Tackling language heterogeneity has been a long-term promise of metaprogramming systems, and of multistage programming in particular. Lightweight Modular Staging (LMS) [39] is a state of the art framework and runtime code generator, providing a library of core components for generating efficient code and embedding DSLs in Scala. Delite [45] promises dramatic productivity improvements for DSL developers, while supporting parallel and heterogeneous execution. We believe this approach is complementary to MLIR, providing a higher-level of abstraction to embed DSLs and implement optimizations through generic metaprogramming constructs.

One step further up into the language syntax, ANTLR [33] is among a class of parser generators that aim to make it easy to develop a new compiler frontend. MLIR currently does not have a general parser generation, no AST construction or modeling functionality. Combining MLIR with a system such as ANTLR could result in reusable compiler libraries from user input through to code generation.

More narrowly construed by their application to machine learning, XLA [57], Glow [40] and TVM [11], address similar heterogeneous compilation objectives. Yet these are rather specific code generation instances starting from a graph abstraction and targeting multi-dimensional vector abstractions for accelerators. All of these could leverage MLIR as infrastructure, taking advantage of the common functionality while using their current code generation strategies. Similarly, the loop nest metaprogramming techniques from Halide [36] and TVM [11], earlier loop nest metaprogramming [19, 41, 5, 14], and fully automatic flows such as PolyMage [28], Tensor Comprehensions [52], Stripe [58], Diesel [16], Tiramisu [4] and their underlying polyhedral compilation techniques [17, 54, 8, 55] could co-exist as different code generation paths within an MLIR-based compilation framework. Serialization and interoperability formats, such as ONNX [48], have a different approach towards addressing the diversity of ML frontends by providing a common set of ops that different frameworks could map on to. ONNX would be a candidate as a dialect in MLIR to which other ops could be lowered to and from.

8 Conclusion and Future Work

We presented MLIR, a flexible and extensible infrastructure for compiler construction. This paper described MLIR's concrete design, demonstrated its applicability to a range of important domains, and described a number of original research and engineering implications.

Looking ahead, we are eager to see how established compiler communities (e.g. the Clang C and C++ compiler) as well domain experts can benefit from the introduction of higher level, language-specific IRs. We are also interested to see if MLIR enables new approaches to teaching the art of compiler and IR design, and hope to see entirely new areas of research catalyzed or accelerated by this infrastructure.

Future directions There are multiple future directions being pursued for MLIR. In the ML and HPC space, these include inferring efficient Op implementations from reference rank-polymorphic specifications with symbolic shapes. It also involves enabling a wider range of data structures (sparse, graphs) and program transformations, bringing together symbolic reasoning, such as automatic differentiation and algorithmic simplification, with more conventional data flow and control flow-based optimizations. Beyond ML and HPC, one may consider MLIR's applicability to other related domains, such as secure compilation, safety-critical systems, data analytics and graph processing, relational query optimization, etc.

Returning to the world of general-purpose languages, an obvious missing front-end is a C++ mid-level representation derived from Clang. Say, a "CIL" similar in spirit to Swift's SIL and Rust's MIR, that would facilitate the optimization of common C++ idioms that currently need to be reconstructed from lowered code (e.g., treating `std::vector` as an array rather than pointer manipulation). Supporting garbage-collected languages, higher-order and polymorphic type systems with type inference in MLIR are open challenges as well.

Exploring parallelism and concurrency constructs in LLVM has been difficult, primarily as the changes required are invasive and not easily layered (e.g., injecting metadata and inspecting all passes to ensure metadata is propagated while losing optimization opportunities as the level of abstraction is too low). With MLIR, parallel constructs can be first-class operations, using regions and parallel idiom-specific verification. This would support higher-level transformations before lowering to, e.g., LLVM where regular transformations can be performed on already lowered code.

Beyond debugging and testing, textual form of IR is also useful for education. Additional tooling to show the interaction of optimizations in high-performance compilation could demystify compilers for new students. IR design is an integral part of developing a new compiler or optimization framework, but many undergraduate compiler curricula do not cover IR design. MLIR provides opportunities for new approaches to such lessons that could be explored.

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