

# MLIR: Scaling Compiler Infrastructure for Domain Specific Computation Albert Cohen

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Abstract—This work presents MLIR, a novel approach to building reusable and extensible compiler infrastructure. MLIR addresses software fragmentation, compilation for heterogeneous hardware, significantly reducing the cost of building domain specific compilers, and connecting existing compilers together.

MLIR facilitates the design and implementation of code generators, translators and optimizers at different levels of abstraction and 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, while identifying the challenges and opportunities posed by this novel design, semantics, optimization specification, system, and engineering. (2) evaluation of MLIR as a generalized infrastructor show research and uning languages, compilers—descr architecture. educational wiginal compilers

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, flowsensitive type checking (e.g. for linear types), and to improve the implementation of the lowering process. Similarly, machine learning systems typically use "ML graphs" as a domainspecific 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, poor debugging implementar

# MLIR Primer

Multi-dimensional Loop IR

Machine Learning IR

Mid-Level IR

Multi-Level IR









C/C++
PyTorch
.
StarPlat

x86\_64

x86\_64

x86\_64

InstCombine SimplifyCFG Reassociate GVN SCCP CorrelatedValuePropagation DeadCodeElimination (DCE) DeadStoreElimination (DSE) AggressiveDCE ConstantPropagation ConstantHoisting EarlyCSE RedundantDbgInstElimination JumpThreading TailDuplication IndVarSimplify StrengthReduce Sinking CodeGenPrepare DemoteRegisterToMemory SimplifyCFG MergedLoadStoreMotion LowerExpectIntrinsic

LoopSimplify LoopRotate LoopUnswitch LoopUnroll LoopUnrollAndJam LoopDeletion LoopInstSimplify LICM LoopIdiomRecognize LoopDistribute LoopFuse LoopInterchange LoopLoadElim LoopPredication LoopReroll LoopSimplifyCFG LoopStrengthReduce LoopVectorize LoopSink LoopFlatten SampleProfileLoader ThinLTO

Mem2Reg SROA MergedLoadStoreMotion GVNHoist GVNHoistSink MemCpyOpt GlobalValueNumbering AlignmentFromAssumptions DSE (DeadStoreElimination) ADCE (AggressiveDCE) LICM LoadStoreVectorizer MergelCmps PartiallyInlineLibCalls Scalarizer CrossDSOCFI MergeFunctions Called Value Propagation EliminateAvailableExternally InlineCostAnalysis HotColdSplitting PartialInlining LowerTypeTests

GlobalOptimizer GlobalDCE FunctionAttrs ArgumentPromotion IPSCCP ConstantMerge DeadArgumentElimination PruneEH Whole Program Devirt LoopVectorize SLPVectorizer VectorCombine InterleavedAccessPass Polly InstrProfiling ObjCARCOpts BDCE DbgValueHistoryCalculator BarrierNoopPass Verifier BlockPlacement

Inliner

AlwaysInliner

MachineLICM MachineCSE MachineGVN MachineCopyPropagation MachineCombiner MachineScheduler RegisterCoalescer PrologEpilogInserter BranchFolding TailDuplication MachineBlockPlacement CodePlacementOpt MachineDominatorTree MachineBranchProbabilityInfo MachineBlockFrequencyInfo PGOInstrumentationGen PGOInstrumentationUse SampleProfile SamplePGO MachineOutliner FunctionReordering CallSiteSplitting

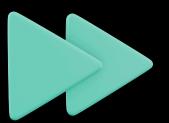
InstructionSelect

### So, what's missing?

We still face several fundamental issues when building modern compilers.



```
function Compute_TC(Graph g) {
  long triangle_count = 0;
  forall(v in g.nodes()) {
    forall(u in g.neighbors(v)) {
        forall(w in g.neighbors(v)) {
            if (g.is_an_edge(u, w)) {
                triangle_count += 1;
            }
        }
    }
   return triangle_count;
}
```



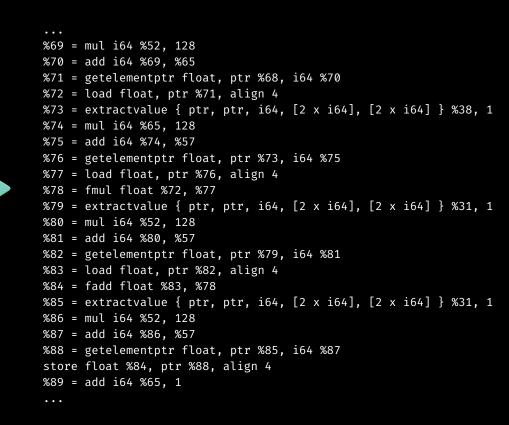
```
%69 = mul i64 %52, 128
%70 = add i64 %69, %65
%71 = getelementptr float, ptr %68, i64 %70
%72 = load float, ptr %71, align 4
%73 = extractvalue { ptr, ptr, i64, [2 x i64], [2 x i64] } %38, 1
%74 = mul i64 %65, 128
%75 = add i64 %74, %57
%76 = getelementptr float, ptr %73, i64 %75
%77 = load float, ptr %76, align 4
%78 = fmul float %72, %77
%79 = extractvalue { ptr, ptr, i64, [2 x i64], [2 x i64] } %31, 1
%80 = mul i64 %52, 128
%81 = add i64 %80, %57
%82 = getelementptr float, ptr %79, i64 %81
%83 = load float, ptr %82, align 4
%84 = fadd float %83, %78
%85 = extractvalue { ptr, ptr, i64, [2 x i64], [2 x i64] } %31, 1
%86 = mul i64 %52, 128
%87 = add i64 %86, %57
%88 = getelementptr float, ptr %85, i64 %87
store float %84, ptr %88, align 4
%89 = add i64 \%65, 1
. . .
```

Vertex2Edge? Auto-Parallelization? Push2Pull?





```
function Compute_TC(Graph g) {
  long triangle_count = 0;
  forall(v in g.nodes()) {
    forall(u in g.neighbors(v)) {
        forall(w in g.neighbors(v)) {
            if (g.is_an_edge(u, w)) {
                triangle_count += 1;
            }
        }
    }
   return triangle_count;
}
```

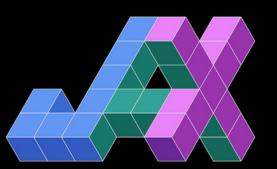


MLIR provides infrastructure to do this!



# Who Uses MLIR?





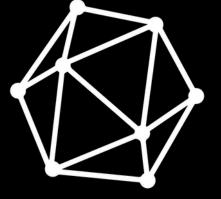














Design Principles

# Little Builtin, Everything Customizable

Minimal Core Concepts

Full Customizability

Reusable Infrastructure

Broad Expressiveness

Ecosystem Discipline

; Keep only the essentials built-in, everything else be custom.

```
module {
  func.func @Compute_TC(%g : !starplat.graph) -> i64 {
   %0 = arith.constant 0
   %triangle_count = memref.alloca i64
    starplat.forall (%v) in (starplat.nodes %g) {
     starplat.forall (%u) in (starplat.neighbors %g, %v) {
        starplat.forall (%w) in (starplat.neighbors %g, %v) {
          %edge_exists = starplat.is_edge %g, %u, %w
          starplat.if %edge_exists {
            %old = memref.load %triangle_count
           %one = arith.constant 1
            %new = arith.add %old, %one
            memref.store %new, %triangle_count
    %ret = memref.load %triangle_count
    func.return %ret
```

#### Attributes

- AffineMapAttr
- ArrayAttr
- DenseArrayAttr
- DenseIntOrFPElementsAttr
- DenseResourceElementsAttr
- DenseStringElementsAttr
- DictionaryAttr
- FloatAttr
- IntegerAttr
- IntegerSetAttr
- OpaqueAttr
- SparseElementsAttr
- o StringAttr
- SymbolRefAttr
- ∘ <u>TypeAttr</u>
- UnitAttr
   StridedLayoutAttr
- Location Attributes
- CallSiteLoc
- ∘ FilcLincColRange
- FusedLoc
- o <u>NameLoc</u>
- o <u>OpaqueLoc</u>
- UnknownLog

### DistinctAttribute

#### Operations

- builtin.module (ModuleOp)
- builtin.unrealized\_conversion\_cast\_(UnrealizedConversionCastOp)

#### Types

- BFloat16Type
- ComplexType
- ∘ Float4E2M1FNType
- Float6E2M3FNType
- Float6E3M2FNType
- Float8E3M4Type
- Float8E4M3Type
   Float8E4M3B11FNUZType
- EL-10E (MOENT---
- Float8E4M3FNType
   Float8E4M3FNUZType
- ∘ Float8E5M2Type
- Float8E5M2FNUZType
- o Float8E8M0ENUType
- Float16Type
- Float32Type
- Float64Type
- ∘ Float80Type
- Float128Type
- FloatTF32Type
- ∘ <u>FunctionType</u>
- GraphType
- ∘ <u>IndexType</u>
- ∘ <u>IntegerType</u>
- ∘ <u>MemRefType</u>
- ∘ <u>NoneType</u>
- <u>OpaqueType</u>
   <u>RankedTensorType</u>
- ∘ <u>TupleType</u>
- UnrankedMemRefType
- UnrankedTensorType
- ∘ <u>VectorType</u>
- Type Interfaces



# Progressive lowering

Multi-Level Abstraction

Step-by-Step Lowering

Extensible Design

**Unified Transformation** 

Pass Interaction

; Enables flexible, multi-level lowering with small, composable steps for optimized performance across abstraction levels.



# Maintain higher-level semantics

Preserve High-Level Abs

Avoid "Raising" Semantics

**Conscious Lowering** 

Mixed Abstraction Levels

Heterogeneous and Parallel

; MLIR preserves semantic and structural information for improved analysis, parallelization, and heterogeneous code generation, lowering it only when necessary.



IR Design Details

# Operations

In MLIR, everything is an operation. Not just instructions, but the entire hierarchy of computation.

Component	Description
Opcode	Unique string: <dialect>.<operation> (e.g., arith.addi)</operation></dialect>
Operands	Input SSA values consumed by the op
Results	Output SSA values produced by the op
Attributes	Immutable metadata (e.g., constants, names, options)
Regions / Blocks	Contain nested operations — enable control flow
Location Info	Source position (for debug, diagnostics)

No fixed set of ops, fully extensible system

Traits & interfaces let passes reason about semantics





### Dialects

Dialects are namespaces that logically group Ops, Types, and Attributes together.

They make MLIR modular, extensible, and organized, like compiler libraries for different domains.

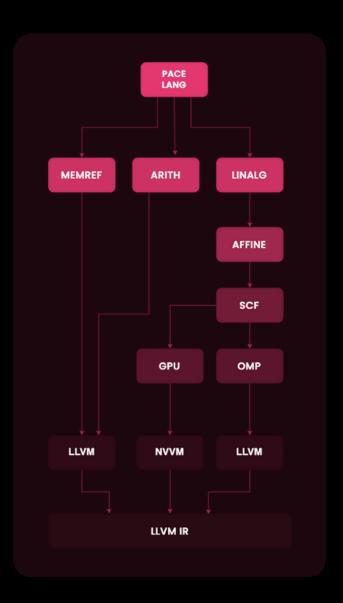
Enable modular compiler design

Let developers define domain-specific abstractions (e.g., Tensor, GPU, Quantum)

Allow progressive lowering

Prevent naming collisions and keep IR organized

Dialects make MLIR truly extensible. You can build your own world of operations and still interoperate with everyone else's.



'acc' Dialect 'smt' Dialect

'affine' Dialect 'sparse\_tensor' Dialect

'amdqpu' Dialect 'tensor' Dialect 'amx' Dialect 'ub' Dialect 'arith' Dialect 'vcix' Dialect 'arm\_neon' Dialect 'vector' Dialect 'arm\_sve' Dialect 'wasmssa' Dialect 'ArmSME' Dialect 'x86vector' Dialect 'async' Dialect 'xegpu' Dialect 'bufferization' Dialect 'xevm' Dialect 'cf' Dialect **Builtin Dialect** 

'complex' Dialect OpInterface definitions

'dlti' Dialect
'emitc' Dialect
'func' Dialect
'gpu' Dialect
'index' Dialect
'memref' Dialect
'ml\_program' Dialect

'irdl' Dialect
'linalg' Dialect
'linalg' Dialect
'livm' Dialect
'math' Dialect
'pdl' Dialect
'ptr' Dialect
'scf' Dialect

'quant' Dialect 'shape' Dialect 'rocdl' Dialect 'shard' Dialect

# Why MLIR Needs Debugging?

```
module {
 func.func @matmul(%arg0: i32, %arg1: i32, %arg2: i32, %arg3:
memref<?x128xf32>, %arg4: memref<?x128xf32>, %arg5: memref<?
x128xf32>) {
   %cst = arith.constant 0.000000e+00 : f32
   %0 = arith.index_cast %arg0 : i32 to index
   %1 = arith.index_cast %arg1 : i32 to index
   %2 = arith.index_cast %arg2 : i32 to index
   affine.for %arg6 = 0 to 128 {
   affine.for %arg7 = 0 to 128 {
   affine.store %cst, %arg5[%arg6, %arg7] : memref<?x128xf32>
   affine.for %arg8 = 0 to 128 {
   %3 = affine.load %arg3[%arg6, %arg8] : memref<?x128xf32>
   %4 = affine.load %arg4[%arg8, %arg7] : memref<?x128xf32>
   %5 = arith.mulf %3, %4 : f32
   %6 = affine.load %arg5[%arg6, %arg7] : memref<?x128xf32>
   %7 = arith.addf %6, %5 : f32
   affine.store %7, %arg5[%arg6, %arg7] : memref<?x128xf32>
  return
```

What value does %arg0 actually hold at runtime? Is my loop even running?

Am I accidentally accessing memory out of bounds?



What you would do in this scenario?

```
module {
func.func @matmul(%arg0: i32, %arg1: i32, %arg2: i32, %arg3:
memref<?x128xf32>, %arg4: memref<?x128xf32>, %arg5: memref<?
x128xf32>) {
  arey.print %arg0 : i32
  %cst = arith.constant 0.000000e+00 : f32
  %0 = arith.index_cast %arg0 : i32 to index
  %1 = arith.index_cast %arg1 : i32 to index
  %2 = arith.index_cast %arg2 : i32 to index
  affine.for %arg6 = 0 to 128 {
  arey.print_str "Hi Here"
   affine.for %arg7 = 0 to 128 {
   affine.store %cst, %arg5[%arg6, %arg7] : memref<?x128xf32>
    affine.for %arg8 = 0 to 128 {
   %3 = affine.load %arg3[%arg6, %arg8] : memref<?x128xf32>
   %4 = affine.load %arg4[%arg8, %arg7] : memref<?x128xf32>
   arey.assert %arg7 : i32 eq 1
  return
```



# Aspect

Domain Specific

Custom Operation

Abstraction Level

Infrastructure Support

## MLIR

Designed to support domain-specific dialects (e.g., Tensor, GPU, Linalg).

Users can define custom operations via dialects.

Multi-level



# LLVM

Not domain-specific; single fixed IR for all domains.

Users can't define custom operations via dialects.

Low-level only





Multi-dimensional Loop IR?

Machine Learning IR?

Mid-Level IR?

Multi-Level IR?

What is MLIR?

# Ongoing works @Gajendra

## **StarPlat MLIR**

MLIR for graph analytics
Operations / Types related to Graph Analytivs
Vertex2Edge , Edge2Vertex, etc



### **DHIR**

Distributed Heterogeneous IR

Orchestrates tasks

Auto parallelization, Task Scheduling, etc



