MLIR
Compiler Construction for Heterogeneity

Cambium Seminar

January 24 2022

Albert Cohen albertcohen@google.com (presenting the work of many)

Personal Background

https://scholar.google.com/citations?user=_KMsPngAAAAJ

https://research.google/people/106208

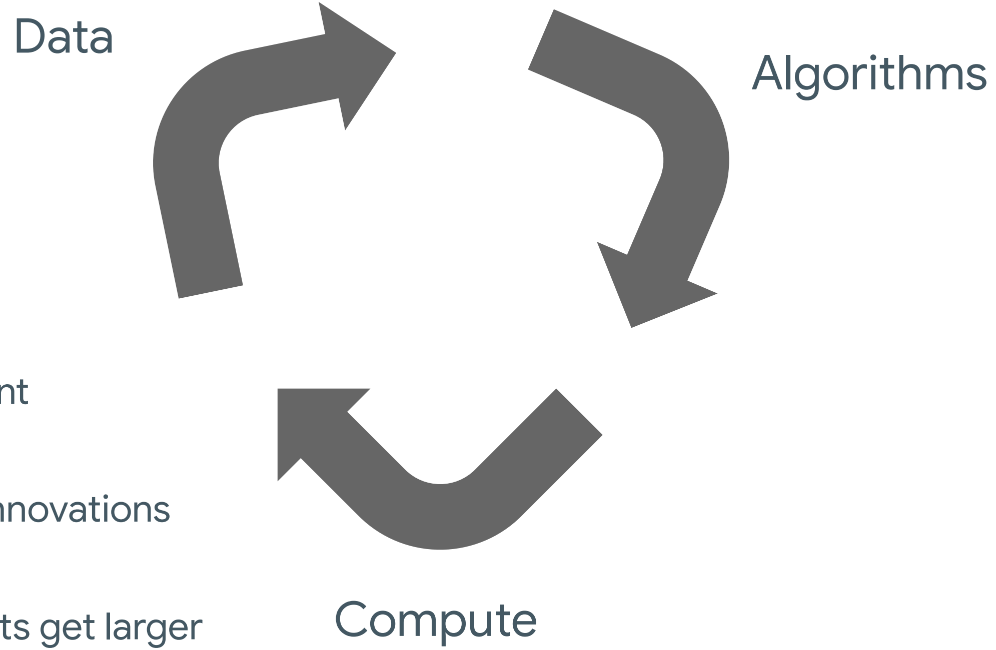
- Parallelizing compilation
- Polyhedral compilation

- Compiler construction
- Machine learning applied to compiler construction

- Data-flow and synchronous programming languages
- Task-parallel programming languages

ML ←?→ Compilers

ML is: Data, Algorithms and Compute



Data drives the continuous improvement cycle for ML models

Researchers provide new algorithmic innovations unlocking new techniques and models

Compute allows it all to scale as datasets get larger and algorithms need to scale on that accordingly

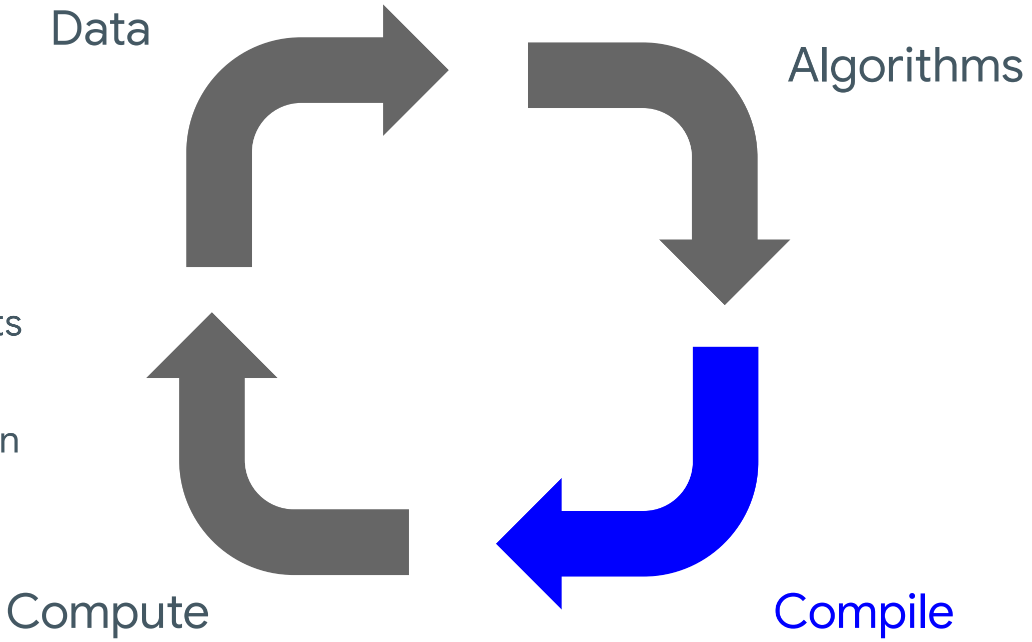
ML is: Data, Algorithms, Compile and Compute

Compilation is key to ML systems performance and portability

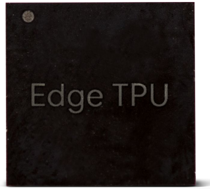
Tensor compilers in particular

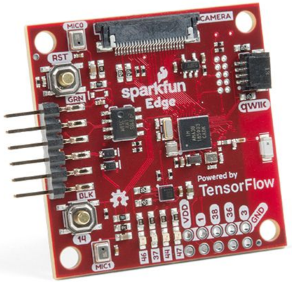
Diversity and competing requirements from users, and hardware

ML is key to solving future compilation problems



Machine Learning SW and HW



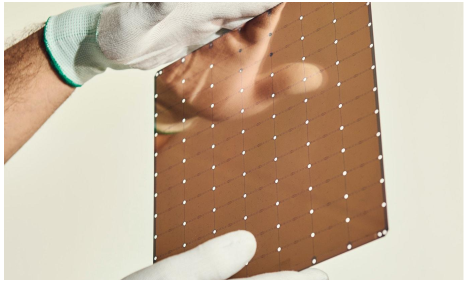


PyTorch

CNTK

mxnet

ONNX



None of this is scaling

Relief from Programming Languages?
Compiler Construction?

MLIR

MLIR:
Scaling Compiler Infrastructure for Domain Specific Computation

CGO, March 1, 2021

Chris Lattner[1,2], Mehdi Amini[1], Uday Bondhugula[1,3], Albert Cohen[1], Andy Davis[1],
Jacques Pienaar[1], River Riddle[1], Tatiana Shpeisman[1], Nicolas Vasilache[1], Oleksandr Zinenko[1]

(and many more MLIR contributors)

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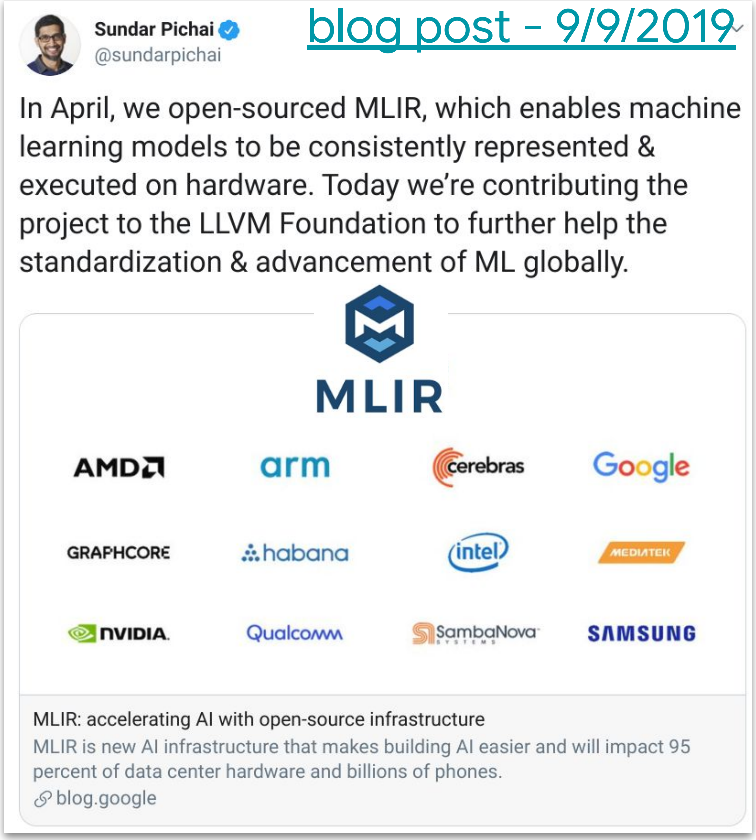
MLIR — Multi-Level Intermediate Representation

[blog post - 9/9/2019]


Sundar Pichai
@sundarpichai

In April, we open-sourced MLIR, which enables machine learning models to be consistently represented & executed on hardware. Today we're contributing the project to the LLVM Foundation to further help the standardization & advancement of ML globally.

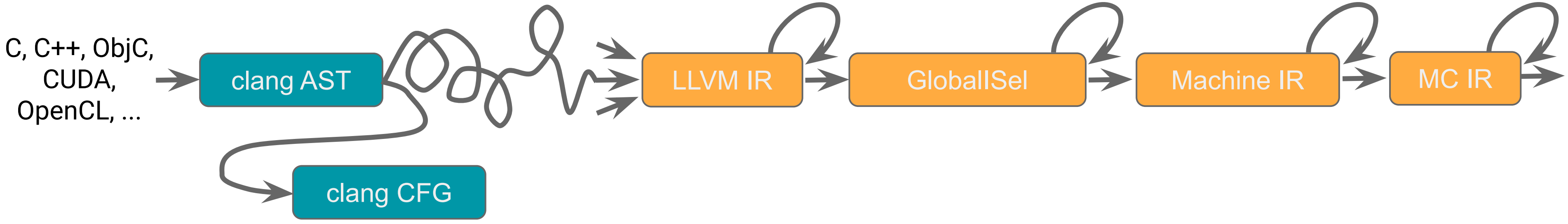
MLIR: accelerating AI with open-source infrastructure
MLIR is new AI infrastructure that makes building AI easier and will impact 95 percent of data center hardware and billions of phones.
blog.google

A collection of modular and reusable software components that enables the progressive lowering of ML operations, to efficiently target hardware in a common way

https://mlir.llvm.org

Why build the (N+1)-th compiler infrastructure?

LLVM: Industry Standard for Compiler Infrastructure



LLVM IR is not enough for high-level representations

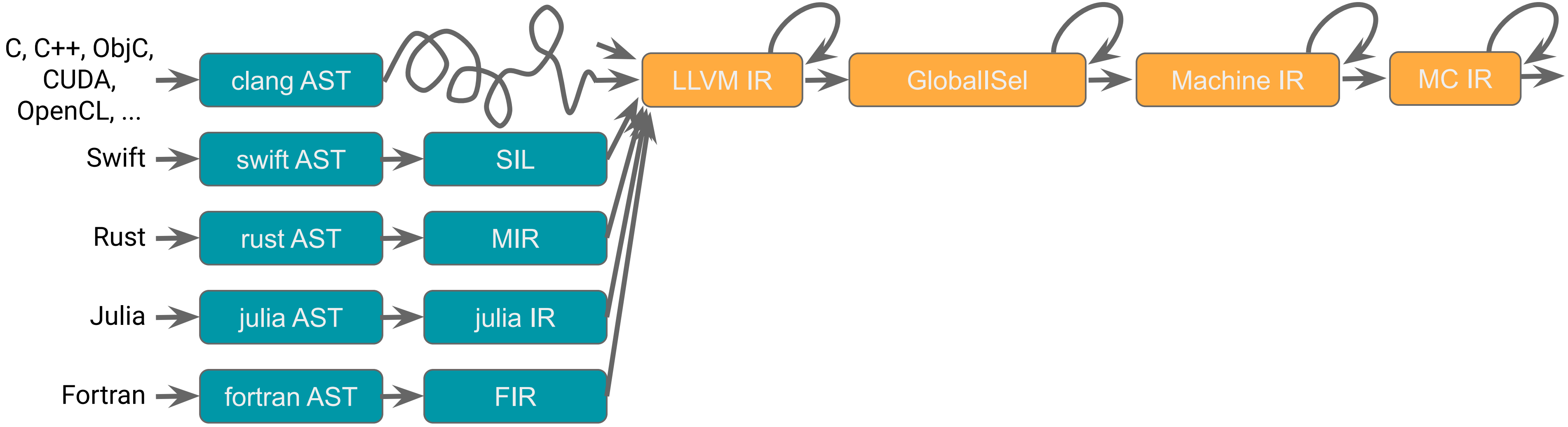
There is a huge abstraction gap between ASTs and LLVM IR, covered in a one-shot conversion in Clang

Clang has a representation parallel to ASTs used in static analyzers, advanced diagnostics

LLVM IR is not enough for low-level representations

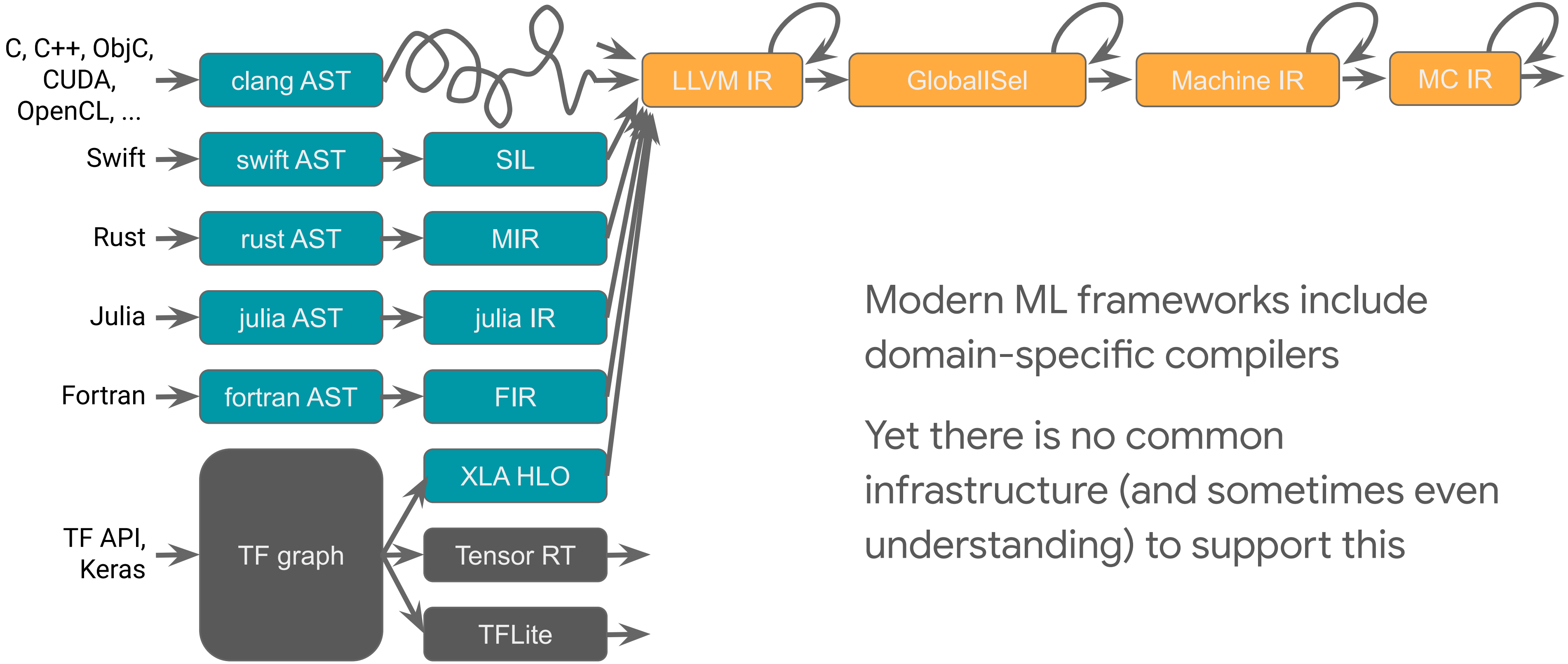
Multiple lower levels of abstraction introduced over time

LLVM: Industry Standard for Compiler Infrastructure



Newer languages/compilers define custom intermediate representations between AST and LLVM IR for language-specific analyses and transformations

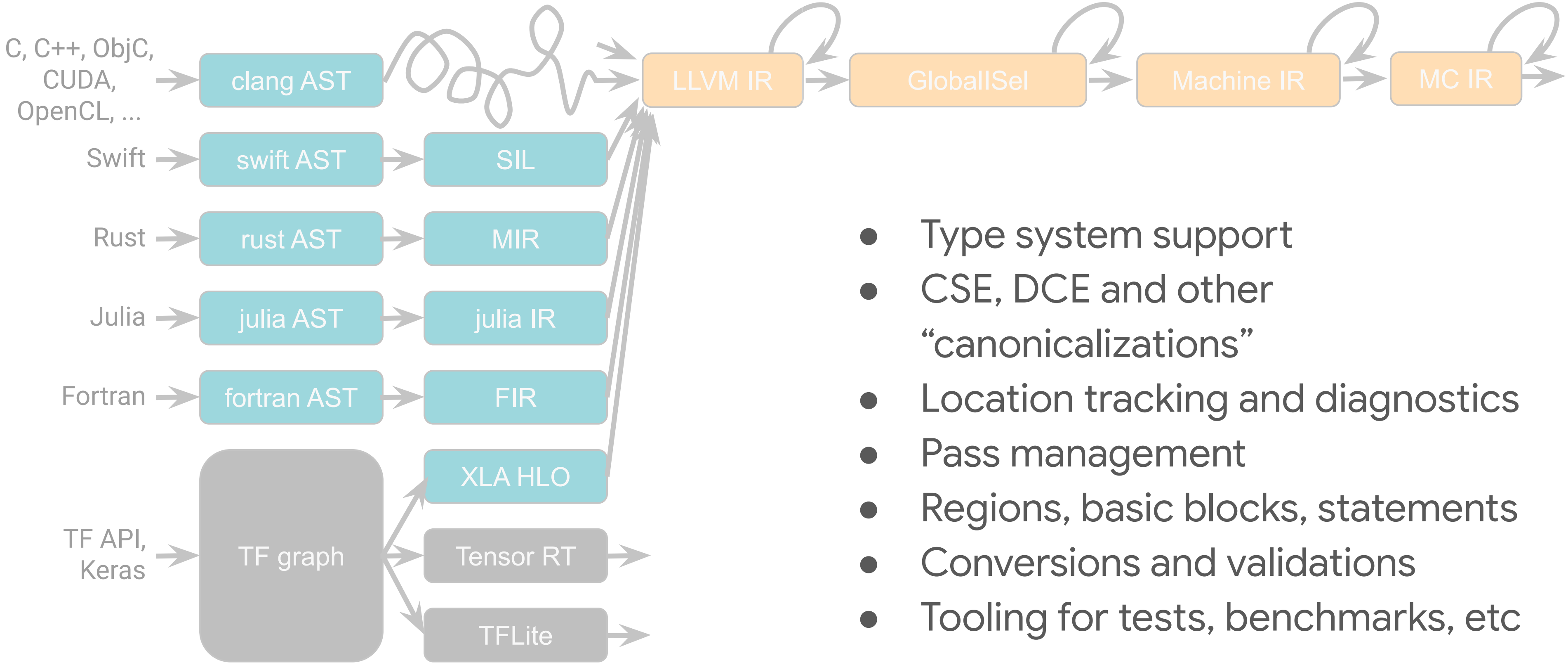
Also Domain-Specific Languages...



Modern ML frameworks include domain-specific compilers

Yet there is no common infrastructure (and sometimes even understanding) to support this

How much code in this picture is unique?



- Type system support
- CSE, DCE and other "canonicalizations"
- Location tracking and diagnostics
- Pass management
- Regions, basic blocks, statements
- Conversions and validations
- Tooling for tests, benchmarks, etc

MLIR Design

Design principles

Parsimony

In compilers, some things are intrinsically complex, avoid making easy things incidentally complex. A small set of versatile built-in concepts enables wide extensibility of the system.

Traceability

It is almost always easier to preserve information than to recover it. Keep the compiler accountable: systematic verification and serializability of the IR. Declarative specification of IR elements and transformations.

Progressivity

In compilers, premature lowering is the predecessor of all evil. Preserve high-level abstractions as long as necessary, lower them consciously. Embrace diverging flows and extensibility. Intermediate state is important in an IR.

Design requirements

Parsimony

- Everything extensible
- SSA graphs + regions

Traceability

- Pervasive source location info
- Declarative specification

Progressivity

- Support high-level abstractions
- Progressive lowering

IR Structure

Operation

Operation is the unit of semantics wrt execution. The semantics of operations specify what is computed and how. There is no fixed set of operations.

Region

A container attached to an operation that can (indirectly) contain other operations. Either SSA dominance-based CFG or graph.

Block

A list of operations contained in a region with no control flow. The last operation in a block is a terminator that can transfer control flow to blocks or regions.

```
%res:2 = "mydialect.morph"(%input#3) { some.attribute : true, other_attribute : 1.5 }
       ({
       ^bb0:
         "mydialect.nested"() : () -> ()
         "mydialect.terminator"() : () -> ()
       })
       : (!mydialect<"custom_type">) -> (!mydialect<"other_type">, !mydialect<"other_type">)
        loc(callsite("foo" at "mysource.cc":10:8))
```

IR Structure

Operation

Operation is the unit of semantics wrt execution. The semantics of operations specify what is computed and how.

Region

A container attached to an operation that can (indirectly) contain other operations. Either SSA dominance-based CFG or data-flow graph. Lexically scoped.

Block

A list of operations contained in a region with no control flow. The last operation in a block is a terminator that can transfer control flow to blocks or regions.

```
%res:2 =                    %input#3  { some.attribute : true, other_attribute : 1.5 }
      ({
      ^bb0:
        "mydialect.nested"() : () -> ()
        "mydialect.terminator"() : () -> ()
      })
      : (!mydialect<"custom_type">) -> (!mydialect<"other_type">, !mydialect<"other_type">)
       loc(callsite("foo" at "mysource.cc":10:8))
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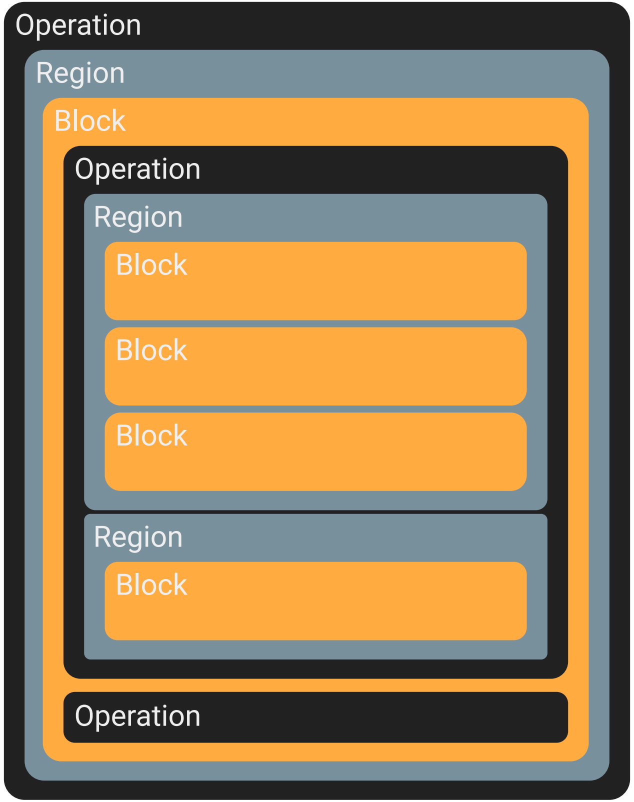
```
%res:2 = "mydialect.morph"(%input#3) { some.attribute : true, other_attribute : 1.5 }
        ({
        ^bb0:
          "mydialect.nested"() : () -> ()
          "mydialect.terminator"()[^bb0] : () -> ()
        })
        : (!mydialect<"custom_type">) -> (!mydialect<"other_type">, !mydialect<"other_type">)
          loc(callsite("foo" at "mysource.cc":10:8))
```

IR Structure is Recursive



IR Objects

Value

Values are units of runtime data. They are defined and used by operations. Values obey static single assignment (SSA) rule. Value names are transient.

Type

Types describe compile-time information about a value. Each value has a type. Operation specifies types of defined and used values. The type system is *open*.

Attribute

Attributes describe compile-time information about an operation. They may be optional or mandatory as per operation semantics. The attribute system is *open*.

```
%res:2 = "mydialect.morph"(%input#3) { some.attribute : true, other_attribute : 1.5 }
       ({
       ^bb0:
         "mydialect.nested"() : () -> ()
         "mydialect.terminator"() : () -> ()
       })
       : (!mydialect<"custom_type">) -> (!mydialect<"other_type">, !mydialect<"other_type">)
        loc(callsite("foo" at "mysource.cc":10:8))
```

IR Extensibility Hooks

Operation

No fixed set of operations. Examples:

- "machine" integer arithmetic;
- saturating integer arithmetic;
- LLVM IR intrinsics (first-class!);
- TensorFlow operations;
- affine loops and conditionals;
- semiconductor circuits, ...

Type

The type system is *open*. Examples:

- *n*D "machine" vectors;
- ranked and unranked tensors;
- all of LLVM IR types;
- functions;
- Fortran types, ...

Attribute

The attribute system is *open*. Examples:

- integer or string values;
- file:line:col locations;
- affine maps;
- opaque AST node pointers;
- binary blobs;
- containers of other attributes, ...

Dialect

Dialects: families of attributes, operations, types

Dialect ~ abstraction level:

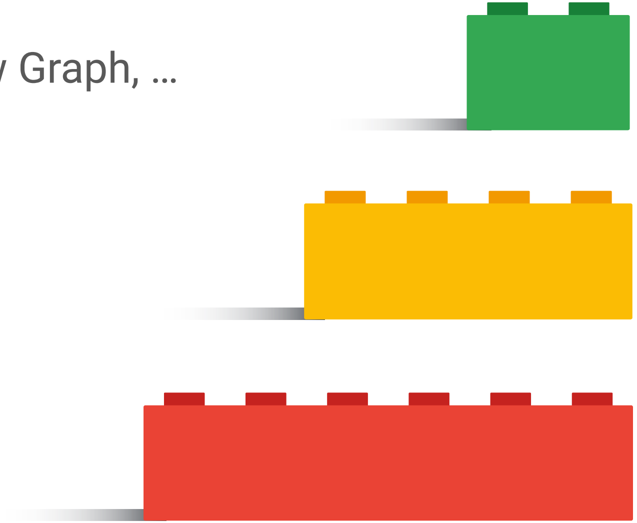
LLVM IR, Fortran FIR, Swift SIL, XLA HLO, TensorFlow Graph, …

A dialect can define:

Operations

Type system(s)

Customization hooks: constant folding, decoding, …



An operation can define:

Invariants on # operands, types, results, attributes, …

Custom parser, printer, verifier, …

Canonicalization patterns, …

Syntax In a Nutshell

Number of values returned

Dialect prefix

Op Id

Argument

Index in the producer's results

List of attributes: constant named arguments

```
%res:2 = "mydialect.morph"(%input#3) { some.attribute = true, other_attribute = 1.5 }
        : (!mydialect<"custom_type">) -> (!mydialect<"other_type">, !mydialect<"other_type">)
                                loc(callsite("foo" at "mysource.cc":10:8))
```

Name of the results

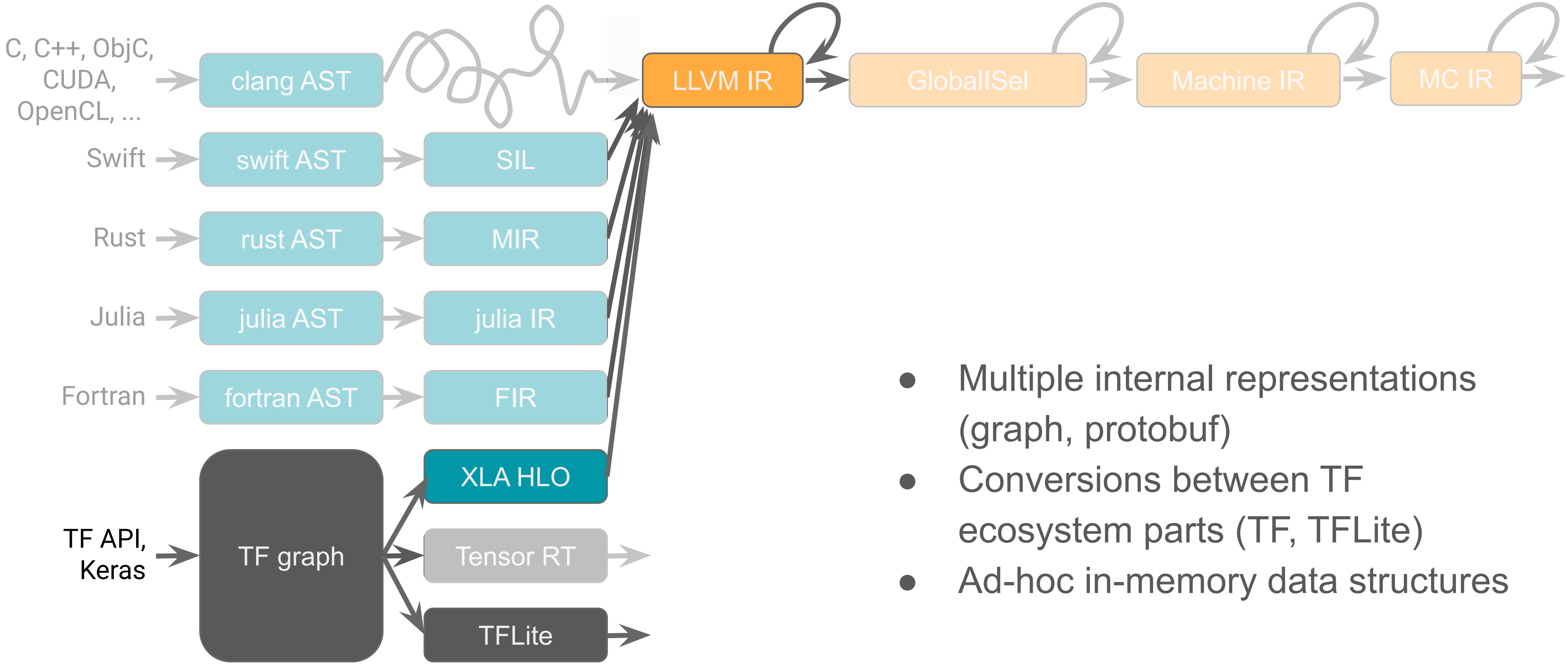
Dialect prefix for the type

Opaque string / Dialect specific type

Mandatory and Rich Location

Users and Uses

TensorFlow



- Multiple internal representations (graph, protobuf)
- Conversions between TF ecosystem parts (TF, TFLite)
- Ad-hoc in-memory data structures

TensorFlow Graphs

```
%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, %2, %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
}
```

TensorFlow Graphs

```
%0 = tf.graph (%arg0 : tensor<f32>, %arg1 : tensor<f32>,
               %arg2 : !tf.resource) {
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      : (tensor<f32>, tensor<f32>) -> (tensor<f32>, !tf.control)
  %control_2 = tf.AssignVariableOp(%arg2, %2, %control)
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  %3, %control_3 = tf.Add(%2, %arg1)
      : (tensor<f32>, tensor<f32>) -> (tensor<f32>, !tf.control)
  tf.fetch %3, %control_2 : tensor<f32>, !tf.control
}
```

Tensors are SSA values: DCE, CSE, etc apply seamlessly

The Graph is an operation with an attached region (no traditional CFG)

TensorFlow Graphs

```
%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
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      : (!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, %2, %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
}
```

Resource modeling
(explicit state, I/O etc.)

TensorFlow Graphs

```
%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.
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      : (!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, %2, %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
}
```

Execution ordering through token-typed values

TensorFlow Graph Lowering: Mix and Match in a Single IR

Lowering

TensorFlow

```
%x = "tf.Conv2d"(%input, %filter)
          {strides: [1,1,2,1], padding: "SAME", dilations: [2,1,1,1]}
    : (tensor<*xf32>, tensor<*xf32>) -> tensor<*xf32>
```

XLA HLO

```
%m = "xla_hlo.AllToAll"(%z)
          {split_dimension: 1, concat_dimension: 0, split_count: 2}
    : (memref<300x200x32xf32>) -> memref<600x100x32xf32>
```

LLVM IR

```
%f = llvm.add %a, %b
    : !llvm.float
```

Polyhedral Optimization

Widely explored in compiler research

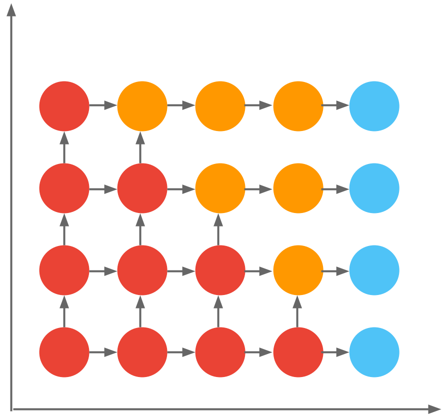
Great success in HPC and image processing kernels.

Tensor abstraction gives full control over memory layout.

Strong mathematical foundation

Powerful loop dependence analysis and loop transformations.

Simplified polyhedral form in MLIR



Polyhedral Optimization

```
func @matmul_square(%A: memref<?x?xf32>, %B: memref<?x?xf32>, %C: memref<?x?xf32>) {
  %zero = constant 0 : f32
  %n = dim %A, 0 : memref<?x?xf32>

  affine.for %i = 0 to %n {
    affine.for %j = 0 to %n {
      affine.store %zero, %C[%i, %j]   : memref<?x?xf32>
      affine.for %k = 0 to %n {
        %a    = affine.load %A[%i, %k] : memref<?x?xf32>
        %b    = affine.load %B[%k, %j] : memref<?x?xf32>
        %prod = mulf %a, %b            : f32
        %c    = affine.load %C[%i, %j] : memref<?x?xf32>
        %sum  = addf %c, %prod         : f32
        affine.store %sum, %C[%i, %j]  : memref<?x?xf32>
      }
    }
  }
  return
}
```

Polyhedral Optimization

```
func @matmul_square(%A: memref<?x?xf32>, %B: memref<?x?xf32>, %C: memref<?x?xf32>) {
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        %prod = mulf %a, %b            : f32
        %c    = affine.load %C[%i, %j] : memref<?x?xf32>
        %sum  = addf %c, %prod         : f32
        affine.store %sum, %C[%i, %j]  : memref<?x?xf32>
      }
    }
  }
  return
}
```

Leverages nD structure of standard types.

Polyhedral Optimization

```
func @matmul_square(                                                    ) {
  %zero = constant 0 : f32
  %n = dim %A, 0 : memref<?x?xf32>

  affine.for %i = 0 to %n {
    affine.for %j = 0 to %n {
      affine.store %zero, %C[%i, %j]   : memref<?x?xf32>
      affine.for %k = 0 to %n {
        %a    = affine.load %A[%i, %k] : memref<?x?xf32>
        %b    = affine.load %B[%k, %j] : memref<?x?xf32>
        %prod = mulf %a, %b            : f32
        %c    = affine.load %C[%i, %j] : memref<?x?xf32>
        %sum  = addf %c, %prod         : f32
        affine.store %sum, %C[%i, %j]  : memref<?x?xf32>
      }
    }
  }
  return
}
```

Leverages nD structure of standard types.

Affine loops are first-class operations; affine constraints are implemented in the verifier.

Polyhedral Optimization

```
func @matmul_square(                                             ) {
  %zero = constant 0 : f32



      affine.store %zero, %C[%i, %j]   : memref<?x?xf32>

        %a    = affine.load %A[%i, %k] : memref<?x?xf32>
        %b    = affine.load %B[%k, %j] : memref<?x?xf32>
        %prod = mulf %a, %b            : f32
        %c    = affine.load %C[%i, %j] : memref<?x?xf32>
        %sum  = addf %c, %prod         : f32
        affine.store %sum, %C[%i, %j]  : memref<?x?xf32>



  return
}
```

Leverages nD structure of standard types.

Affine loops are first-class operations; affine constraints are implemented in the verifier.

Load/store operations accept affine maps.

Polyhedral Optimization

```
func @matmul_square(                                                              ) {
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  %n = dim %A, 0 : memref<?x?xf32>



      affine.store %zero, %C[%i, %j]   : memref<?x?xf32>



        %prod = mulf %a, %b            : f32
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        %sum  = addf %c, %prod         : f32




  return
}
```

Leverages nD structure of standard types.

Affine loops are first-class operations; affine constraints are implemented in the verifier.

Load/store operations accept affine maps.

Introduce operations from other dialects for computation.

Unified Accelerator and Host Representation

```
llvm.mlir.global internal @global(42 : i64) : !llvm.i64

func @some_func(%arg0 : memref<?xf32>) {
  %cst = constant 8 : index
  gpu.launch blocks(%bx, %by, %bz) in (%grid_x = %cst, %grid_y = %cst,
                                       %grid_z = %cst)
             threads(%tx, %ty, %tz) in (%block_x = %cst, %block_y = %cst,
                                        %block_z = %cst) {
    gpu.call @device_function() : () -> ()
    %0 = llvm.mlir.addressof @global : !llvm<"i64*">
    gpu.return
  }
  return
}

gpu.func @device_function() {
  gpu.call @recursive_device_function() : () -> ()
  gpu.return
}
gpu.func @recursive_device_function() {
  gpu.call @recursive_device_function() : () -> ()
  gpu.return
}
```

Structured Ops

High-performance codegen approach based on ***keeping high-level information available in the IR***

- A way to represent operations in the IR that makes them ***easy to analyze and transform***
  - e.g. matmul, kfac, conv, pointwise etc -> configurations of a “generic custom op”
    - TC/einsum-like definition encoded in the IR but much more powerful:
      - Matmul -> `C(i, j) += A(i, k) + B(k, j)`
      - Conv1d -> `O(n, w, f) += I(n, w + kw, c) * K(kw, c, f)`

Structured Ops

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            - Conv1d -> `O(n, w, f) += I(n, w + kw, c) * K(kw, c, f)`
- A way to decouple op specification from the data type it operates on:
    - `matmul(%a: sparse_tensor<4x?xf32, #CSC>, %b: tensor<?x8xf32>, c: tensor<4x8xf32>)-> (tensor<4x8xf32>)`
    - `matmul(%a: buffer<4x?xf32>, %b: buffer<?x8xf32>, c: buffer<4x8xf32>)`
    - `matmul(%a: vector<4x16xf32>, %b: vector<16x8xf32>, c: vector<4x8xf32>)-> (vector<4x8xf32>)`

Structured Ops

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- A way to decouple op specification from the data type it operates on:
  - `matmul(%a: sparse_tensor<4x?xf32, #CSC>, %b: tensor<?x8xf32>, c: tensor<4x8xf32>)->(tensor<4x8xf32>)`
  - `matmul(%a: buffer<4x?xf32>, %b: buffer<?x8xf32>, c: buffer<4x8xf32>)`
  - `matmul(%a: vector<4x16xf32>, %b: vector<16x8xf32>, c: vector<4x8xf32>) -> (vector<4x8xf32>)`
- A way to decouple op specification from the control flow required to implement it
  - `matmul(%a: buffer<4x?xf32>, %b: buffer<?x8xf32>, c: buffer<4x8xf32>)->(buffer<4x8xf32>)`
    - `Implies a 3-D control-flow iteration space of size 4x?x8`

What does this look like?


```
// linalg.sdot computes C += A(i) * B(i)
linalg.sdot ins(%A, %B: memref<4xf32>, memref<4xf32>) outs(%C: memref<f32>)
```

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linalg.sdot ins(%A, %B: memref<4xf32>, memref<4xf32>) outs(%C: memref<f32>)

%c0 = arith.constant 0: index
%c1 = arith.constant 1: index
%d0 = memref.dim %A, %c0: memref<4xf32>
scf.for %i = %c0 to %d0 step %c1 {
  %lhs_subset = subset %A(@%i, sz=1):
       memref<4xf32> to memref<f32>
  %rhs_subset = subset %B(@%i, sz=1):
       memref<4xf32> to memref<f32>
  %acc_subset = subset %C(@%i, sz=1):
       memref<f32> to memref<f32>
  linalg.sdot ins(%lhs_subset, %rhs_subset:
       memref<4xf32>, memref<4xf32>)
      outs(%acc_subset: memref<f32>)
}
```

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       memref<4xf32> to memref<f32>
  %rhs_subset = subset %B(@%i, sz=1):
       memref<4xf32> to memref<f32>
  %acc_subset = subset %C(@%i, sz=1):
       memref<f32> to memref<f32>
  linalg.sdot ins(%lhs_subset, %rhs_subset:
       memref<4xf32>, memref<4xf32>)
      outs(%acc_subset: memref<f32>)
}
```

```
%c0 = arith.constant 0: index
%c1 = arith.constant 1: index
%d0 = memref.dim %A, %c0: memref<4xf32>
scf.for %i = %c0 to %d0 step %c1 {
  %lhs = memref.load %A[%i]: memref<4xf32>
  %rhs = memref.load %B[%i]: memref<4xf32>
  %acc = memref.load %C[]: memref<f32>
  %tmp = math.mulf %lhs, %rhs: f32
  %res = math.addf %acc, %tmp: f32
  %acc = memref.store %res, %C[]: memref<f32>
}
```

Transformations

Tile, Fuse, Interchange, Multi-Level Vectorize, Bufferize, Pipeline, etc etc etc

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```
DoubleTilingExpert(
    'matmul_on_tensors',
    'linalg.matmul',
    sizes1=[256, 128, 256],
    interchange1=[1, 2, 0],
    peel1=False,
    pad1=False,
    pack_padding1=[],
    hoist_padding1=[0],
    sizes2=[8, 16, 32],
    interchange2=[0, 1, 2],
    peel2=False,
    pad2=True,
    pack_padding2=[0, 1],
    hoist_padding2=[3, 4])
```

Every value is a tunable knob

Sparse code generation

- Tensor Linear Algebra Compiler (TACO)
- Particularly interesting for its flexibility in sparse code generation

```
Format csr({Dense,Sparse});
Tensor<double> A({64,42}, csr);

Format csf({Sparse,Sparse,Sparse});
Tensor<double> B({64,42,512}, csf);

Format svec({Sparse});
Tensor<double> c({512}, svec);

B.insert({0,0,0}, 1.0);
B.insert({1,2,0}, 2.0);
B.insert({1,2,1}, 3.0);
B.pack();

c.insert({0}, 4.0);
c.insert({1}, 5.0);
c.pack();

IndexVar i, j, k;
A(i,j) = B(i,j,k) * c(k);

A.compile();
A.assemble();
A.compute();
```

Fig. 12. Computing tensor-times-vector with the taco C++ library.

```
$taco "A(i,j) = B(i,j,k) * c(k)" -f=A:ds -f=B:sss -f=c:s
// ...
int pA2 = A2_pos[0];
for (int pB1 = B1_pos[0]; pB1 < B1_pos[1]; pB1++) {
  int i = B1_idx[pB1];
  for (int pB2 = B2_pos[pB1]; pB2 < B2_pos[pB1+1]; pB2++) {
    int j = B2_idx[pB2];
    double tk = 0.0;
    int pB3 = B3_pos[pB2];
    int pc1 = c1_pos[0];
    while ((pB3 < B3_pos[pB2+1]) && (pc1 < c1_pos[1])) {
      int kB = B3_idx[pB3];
      int kc = c1_idx[pc1];
      int k = min(kB, kc);
      if (kB == k && kc == k) {
        tk += B_vals[pB3] * c_vals[pc1];
      }
      if (kB == k) pB3++;
      if (kc == k) pc1++;
    }
    A_vals[pA2] = tk;
    pA2++;
  }
}
```

Fig. 13. Using the taco command-line tool to generate C code that computes tensor-times-vector. The output of the command-line tool is shown after the first line. Code to initialize tensors is elided.

Fredrik Kjolstad, Shoaib Kamil, Stephen Chou, David Lugato, and Saman Amarasinghe. The tensor algebra compiler. Proc. ACM Program. Lang. 1, OOPSLA, Article 77 (October 2017)

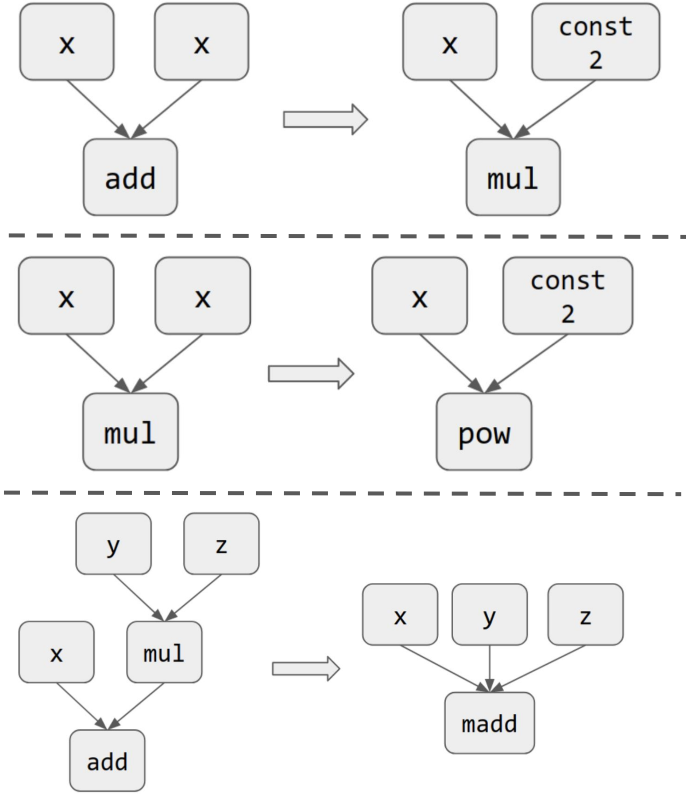
Sparse code generation in MLIR: Sparsity as a Property

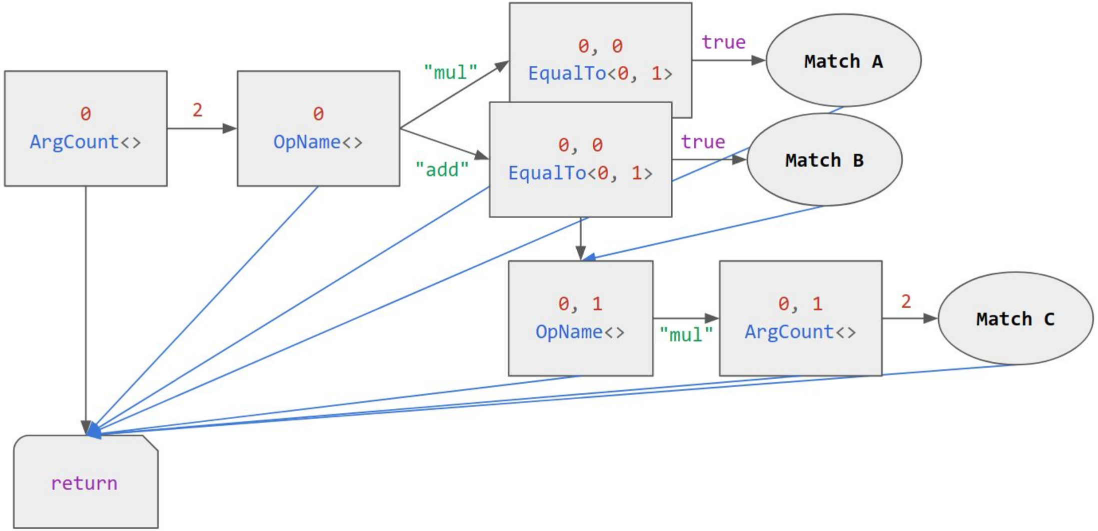
```
#trait_matvec = {
  indexing_maps = [
    affine_map<(i,j) -> (i,j)>,  // A
    affine_map<(i,j) -> (j)>,    // x
    affine_map<(i,j) -> (i)>     // b
  ],
  // Per-tensor, per-dimension annotation
  sparse = [
    [ "D", "S" ],  // A
    [ "D" ],       // x
    [ "D" ]        // b
  ],
  iterator_types = [
    "parallel",
    "reduction"
  ],
  doc = "b(i) += A(i,j) * x(j)"
}
```

```
func @matvec(%argA: tensor<16x32xf32>,
             %argx: tensor<32xf32>,
             %argb: tensor<16xf32>)
                  -> tensor<16xf32> {
  %0 = linalg.generic #trait_matvec
      ins(%argA, %argx :
        tensor<16x32xf32>,
        tensor<32xf32>)
     init(%argb : tensor<16xf32>) {
        ^bb(%A: f32, %x: f32, %b: f32):
            %0 = mulf %A, %x : f32
            %1 = addf %0, %b : f32
            linalg.yield %1 : f32
      } -> tensor<16xf32>
    return %0 : tensor<16xf32>
}
```

MLIR Pattern Matching and Rewrite

~ Instruction Selection problem.





MLIR Pattern Matching and Rewrite

An MLIR dialect to manipulate MLIR IR

```
func @matcher(%0 : !Operation) {
^bb0:
  CheckArgCount(%0) [^bb1, ^ex0] {count = 2}
        : (!Operation) -> ()
^bb1:
  CheckOpName(%0) [^bb2, ^bb5] {name = "add"}
        : (!Operation) -> ()
^bb2:
  %1 = GetOperand(%0) {index = 0} : (!Operation) -> !Value
  %2 = GetOperand(%0) {index = 1} : (!Operation) -> !Value
  ValueEqualTo(%1, %2) [^rr0, ^bb3] : (!Value, !Value) -> ()
^rr0:
  // Save x
  RegisterResult(%1) [^bb3] {id = 0} : (!Value) -> ()
^bb3:
  %3 = GetDefiningOp(%2) : (!Value) -> !Operation
  CheckOpName(%3) [^bb4, ^bb5] {name = "mul"}
        : (!Operation) -> ()
^bb4:
  CheckArgCount(%3) [^rr1, ^bb5] {count = 2}
        : (!Operation) -> ()
```

```
^rr1:
  // Save x, y, and z
  %4 = GetOperand(%3) {index = 0} : (!Operation) -> !Value
  %5 = GetOperand(%4) {index = 1} : (!Operation) -> !Value
  RegisterResult(%1, %4, %5) [^bb5] {id = 1}
        : (!Value, !Value, !Value) -> ()
^bb5:
  // Previous calls are not necessarily visible here
  %6 = GetOperand(%0) {index = 0} : (!Operation) -> !Value
  %7 = GetOperand(%0) {index = 1} : (!Operation) -> !Value
  ValueEqualTo(%6, %7) [^bb6,  ^ex0] : (!Value, !Value) -> ()
^bb6:
  CheckOpName(%0) [^rr2, ^ex0] {name = "mul"}
        : (!Operation) -> ()
^rr2:
  // Save x
  RegisterResult(%6) [^ex0] {id = 2} : (!Value) -> ()
^ex0:
  return
}
```

Implications of MLIR Design

Designing Abstractions for Reuse

Traits

Many transformations need not care about specific operations, but can be expressed on generic traits. Establish operation/transform contracts.

Interfaces

Good old OOP is helpful to specialize pass behavior for specific operations. E.g., operations that know how to constant-fold themselves implement an interface.

Passes

Generic passes may be expressed on traits and interfaces. Dialect-specific passes are a great tool to perform domain-specific transformations.

Example: Loop-Invariant Code Motion

Top-Level Op Structure

An operation with regions.
No need to know if it's an affine "for", a C-like "while", or anything else.

"Loop-Like" Op Interface

Functions to:
- check if a value is defined outside the loop (not necessarily a flat SSA CFG);
- get the loop body region;
- hoist operations out of the body.

Nested Op Traits

- Has no side effects (extensible to side-effects interface);
- Has recursive side effects.

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For all loop-like operations:
 Get the body and for all operations in it:
  Ignore operations with side effects (no traits);
  Ignore operations *containing* side-effecting operations;
  If all operands are defined outside the loop:
   Hoist out of the body;
   On next iterations, the hoisted values are defined outside.

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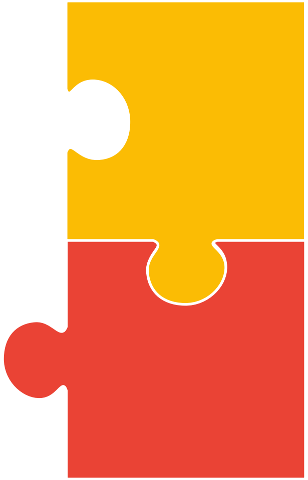
Designing Abstractions for Composition

Mixing Dialects

Dialects are not necessarily hermetic. Reuse other abstractions when possible and deconstruct larger dialects if needed. Always assume abstractions co-exist.

External Interoperability

External formats are messy, often binary or otherwise hard to test. Map them to a dialect and make the translation as simple as possible, then transform within MLIR.



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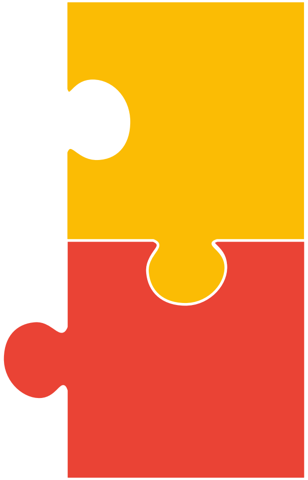

What the future holds

Driving HW/SW Research

Domain and HW-specific IRs

Domain-specific constructs represented as MLIR dialects, leveraged by advanced transformations. No separation between “instructions” and “intrinsics”, support entire ISAs as target dialects. Hardware design as software problem.

Extensible Type Systems

Build and experiment with unconventional data types (quantized numbers or mixed-precision floating point).
More expressive type systems from functional languages, separation logic, borrow checking.

Built for Optimization

Transformation-driven IR abstractions: algorithm specifications vs. schedules. Fast sub-polyhedral abstractions. Various parallelism models, including asynchronous. Search-based program optimization.

Search and ML for Compilers

Expose Compiler Knobs

Separate implementations of program transformations from compiler heuristics. Give control to the expert user or to external tools to enable cross-pollination between compiler and ML research.

Tackle NP-hard Problems

Replace handwritten heuristics, which are often suboptimal and expensive to deploy, with learned transformation strategies. Prepare for the “jungle” of upcoming hardware by automating (re)optimization.

Summary

MLIR Is Changing Compiler Construction

Minimalist Principles

MLIR is a novel compiler infrastructure based on the principles of:
- Parsimony;
- Traceability;
- Progressivity

supporting unprecedented extensibility.

Flexible Core Concepts

The built-in IR concepts:
- Nested structure of operations, regions, blocks;
- Operating on typed (SSA) values and attributes

allow for expressing various abstractions.

Reusable Transformations

Rethink compiler transformations in terms of abstract *properties* of operations rather than exhaustive lists.

Mix-and-match different abstractions, easy to experiment.

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Getting involved

MLIR is Open-Source within LLVM project

MLIR is available

Code: https://mlir.dev/src
Forum: https://mlir.dev/forum
Chat: https://mlir.dev/chat
Main: https://mlir.dev

MLIR is designed for out-of-tree users

Most examples in this presentation are out of LLVM code tree.

Interested? mlir-hiring@google.com

Google Brain PAR/ZRH — C2L2C

Compile to Learn

High-performance ML layers, generated automatically

Compilation algorithms tailored for tensor computing

Learn to Compile

Automatic construction of profitability models, heuristics

Heuristics, performance auto-tuning