Polyhedral Compilation Opportunities in MLIR

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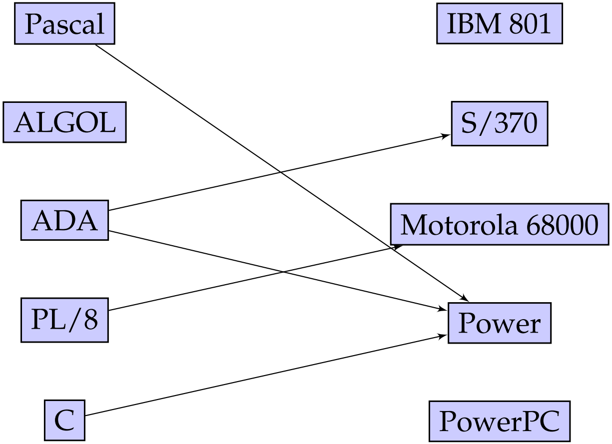
Outline

Compilers - The Early Days



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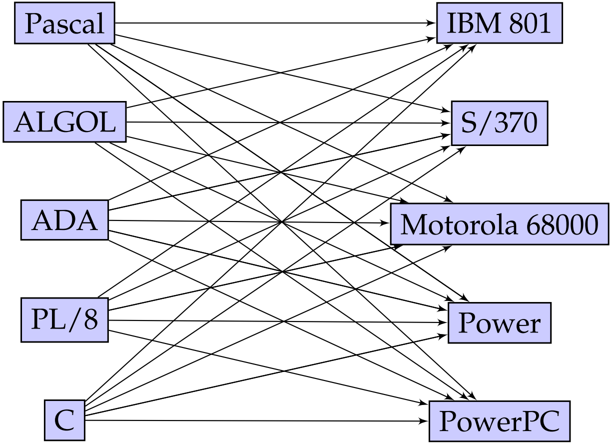
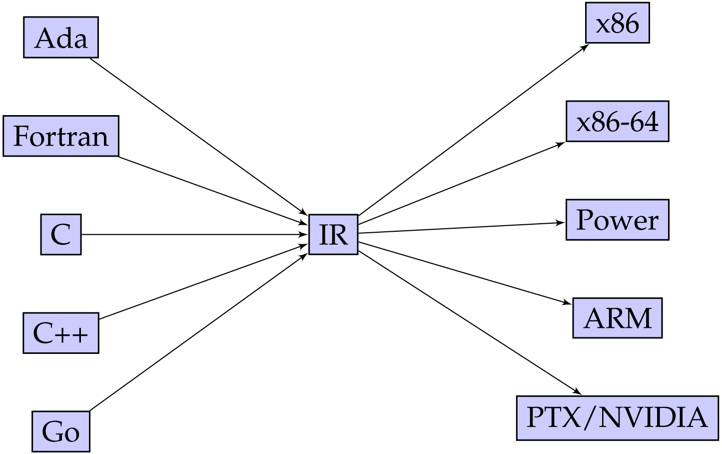


- M **languages,** N **targets** $\Rightarrow M * N$ **compilers! Not scalable!**

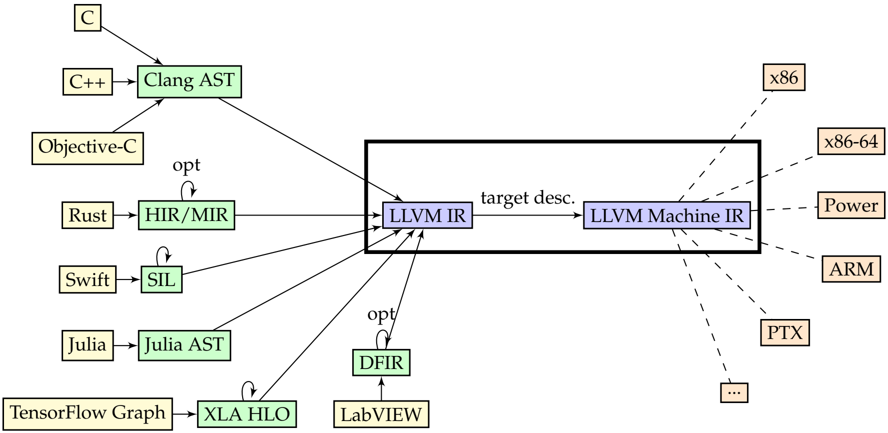
Compilers Evolution - $M + N$



- **With an common IR, we have $M + N + 1$ compilers!**

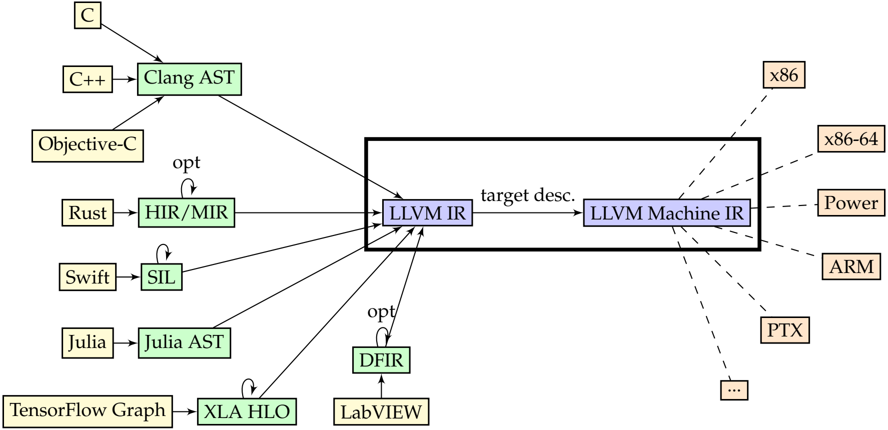
- **How do modern compilers look?**

Modern Compilers - LLVM IR based



- **LLVM: modular, reusable, open-source:** $M + 1 + 1 + N/k$

Modern Compilers - LLVM IR based



- **But too level for ML/AI programming models/hardware**

Fast Forward to ML/AI

- Fast forward to ML/AI compute era

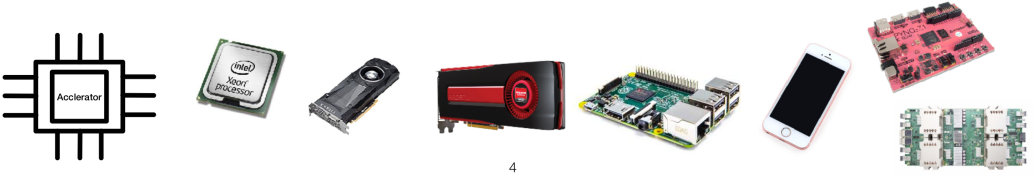
ML / AI Compilation Problem

Explosion of ML/AI programming models, languages, frameworks

. . . ?

Compiler Infrastructure?

Explosion of AI chips and accelerators



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As a result: a proliferation IRs

- **A proliferation of IRs**

- **TensorFlow graphs (Google)**
- **XLA IR / HLO (Google)**
- **Onnx (Facebook, Microsoft)**
- **Glow (Facebook)**
- **Halide IR, TVM (universities)**
- **Stripe (PlaidML, now Intel)**
- **nGraph (Intel)**
- **...**

Explosion of ML/AI programming models, languages, frameworks

. . . ?

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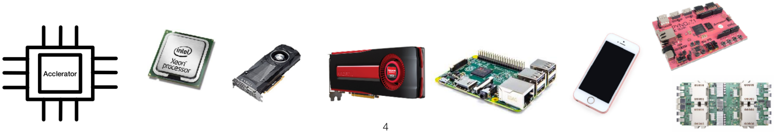
Explosion of AI chips and accelerators



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Explosion of ML/AI programming models, languages, frameworks

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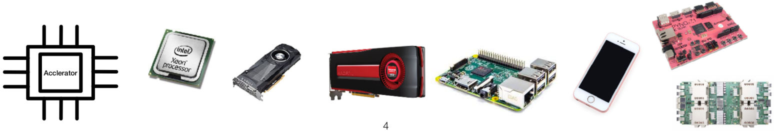
MLIR

Explosion of AI chips and accelerators



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In Comes MLIR

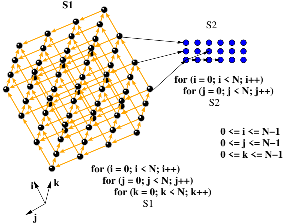
- **Open-sourced by Google in Apr 2019**
- **Designed and built as an IR from day 0!**

MLIR: Multi-level Intermediate Representation

1. Ops (general purpose to domain specific) on tensor types / memref types

```
%patches = "tf.reshape"(%patches, %minus_one, %minor_dim_size)
                  : (tensor<? x ? x ? x ? x f32>, index, index) −> tensor<? x ? x f32>
%mat_out = "tf.matmul"(%patches_flat, %patches_flat){transpose_a : true}
                  : (tensor<? x ? x f32>, tensor<? x ? x f32>) −> tensor<? x ?
                  x f32>
%vec_out = "tf.reduce_sum"(%patches_flat) {axis: 0}
                  : (tensor<? x ? x f32>) −> tensor<? x f32>
```

2. Loop-level / mid-level form




```
affine.for %i = 0 to 8 step 4 {
  affine.for %j = 0 to 8 step 4 {
    affine.for %k = 0 to 8 step 4 {
      affine.for %ii = #map0(%i) to #map1(%i) {
        affine.for %jj = #map0(%j) to #map1(%j) {
          affine.for %kk = #map0(%k) to #map1(%k) {
            %5 = affine.load %arg0[%ii, %kk] : memref<8x8xvector<64xf32>>
            %6 = affine.load %arg1[%kk, %jj] : memref<8x8xvector<64xf32>>
            %7 = affine.load %arg2[%ii, %jj] : memref<8x8xvector<64xf32>>
            %8 = mulf %5, %6 : vector<64xf32>
            %9 = addf %7, %8 : vector<64xf32>
            affine.store %9, %arg2[%ii, %jj] : memref<8x8xvector<64xf32>>
          }
        }
      }
    }
  }
}
```

3. Low-level form: closer to hardware

```
%v1 = load %a[%i2, %i3] : memref<256x64xvector<16xf32>>
%v2 = load %b[%i2, %i3] : memref<256x64xvector<16xf32>>
%v3 = addf %v1, %v2 : vector<16xf32>
store %v3, %d[%i2, %i3] : memref<256x64xvector<16xf32>>
```

MLIR Design Principles / Features

1. Round-trippable textual format
2. Ability to represent code at multiple levels
3. Unified representation for all the levels
4. First class abstractions for multi-dimensional arrays (tensors), loop nests, and more
5. Very flexible, extensible

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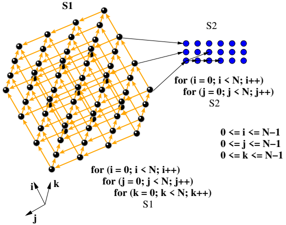
          : (tensor<? x ? x f32>, memref<? x ? x f32>) -> tensor<? x ? x f32>
%vec_out = "tf.reduce_sum"(%patches_flat) {axis: 0}
          : (tensor<? x ? x f32>) -> tensor<? x f32>
```

2. **Loop-level / mid-level form**

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      %8 = mulf %5, %6 : vector<64xf32>
      %9 = addf %7, %8 : vector<64xf32>
      store %9, %arg2[%ii, %jj] : memref<8x8xvector<64xf32>>
     }
    }
   }
  }
 }
}
```

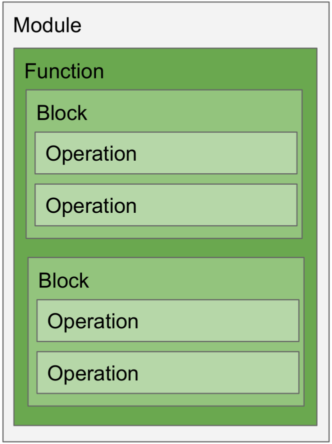
3. **Low-level form: closer to hardware**

```
%v1 = load %a[%i2, %i3] : memref<256x64xvector<16xf32>>
%v2 = load %b[%i2, %i3] : memref<256x64xvector<16xf32>>
%v3 = addf %v1, %v2 : vector<16xf32>
store %v3, %d[%i2, %i3] : memref<256x64xvector<16xf32>>
```

MLIR - Basic Concepts

- SSA, typed
- Module/Function/Block/Operation structure
- Operations can hold a "region" (a list of blocks)

```
func @testFunction(%arg0: i32) {
  %x = call @thingToCall(%arg0) : (i32) −> i32
  br ^bb1
^bb1:
  %y = addi %x, %x : i32
  return %y : i32
}
```



SSA representation

- Functional SSA representation
- No ϕ nodes
- Instead, basic blocks take arguments

```
func @condbr_simple() -> (i32) {
  %cond = "foo"() : () -> i1
  %a = "bar"() : () -> i32
  %b = "bar"() : () -> i64
  cond_br %cond, ^bb1(%a : i32), ^bb2(%b : i64)

^bb1(%x : i32):
  %w = "foo_bar"(%x) : (i32) -> i64
  br ^bb2(%w: i64)

^bb2(%y : i64):
  %z = "abc"(%y) : (i64) -> i32
  return %z : i32
}
```

MLIR Operations

- Operations always have a name and source location info
- Operations may have:
  - Arbitrary number of SSA operands and results
  - Attributes: guaranteed constant values
  - Regions

```
%2 = dim %1, 1 : tensor<1024x? x f32>
// Dimension to extract is guaranteed integer constant, an attribute
%x = alloc() : memref<1024x64 x f32>
%y = load %x[%i, %j] : memref<1024x64 x f32>
```

Ops with Regions

- Operations in MLIR can have nested regions

```
func @loop_nest_unroll(%arg0: index) {
  affine.for %arg1 = 0 to 100 step 2 {
    affine.for %arg2 = 0 to #map1(%arg0) {
      %0 = "foo"() : () -> i32
    }
  }
  return
}
```

- Use cases: besides affine for/if, shielding inner control flow, closures/lambdas, parallelism abstractions like OpenMP, etc.

DIALECTS IN MLIR

- **Dialect**: A collection of operations, types, and attributes suitable for a specific task
- Typically corresponds to a programming model's entry point into MLIR, a backend, or a well-defined abstraction
- Example dialects: TensorFlow dialect, NGraph dialect, Affine dialect, Linalg dialect, NVIDIA GPU dialect, LLVM dialect
- You can have a mix of dialects

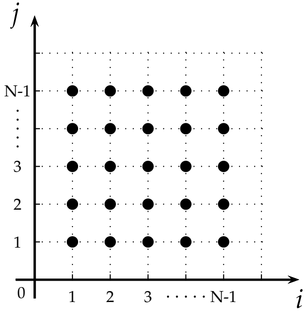
Outline

Polyhedral Framework

```
for (t = 0; t < T; t++)
 for (i = 1; i < N+1; i++)
  for (j = 1; j < N+1; j++)
   A[(t+1)%2][i][j] = f((A[t%2][i+1][j], A[t%2][i][j], A[t%2][i-1][j],
       A[t%2][i][j+1], A[t%2][i][j-1]);
```

1. **Domains**
   - Every statement has a domain or an index **set –** instances that have to be executed
   - Each instance is a vector (of loop index values from outermost to innermost)
     $D_S = \{[t, i, j] \mid 0 \leq t \leq T - 1,\ 1 \leq i, j \leq N\}$
2. **Dependences**
   - A dependence is a **relation** between domain / index set instances that are in conflict (more on next slide)
3. **Schedules**
   - are **functions** specifying the *order* in which the domain instances should be executed
   - Eg: $T((t, i, j)) = (t, t + i, j)$

```
for (i = 1; i <= N - 1; i++)
  for (j = 1; j <= N - 1; j++)
    A[i][j] = f(A[i-1][j], A[i][j-1]);
```

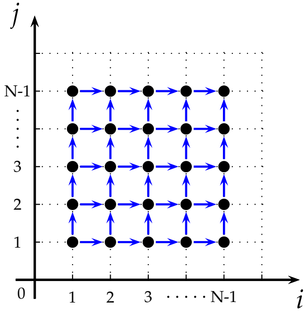


Original space (i, j)

- **Domain**: $\{[i, j] \mid 1 \leq i, j \leq N - 1\}$

Domains, Dependences, and Schedules

```
for (i = 1; i <= N - 1; i++)
  for (j = 1; j <= N - 1; j++)
    A[i][j] = f(A[i-1][j], A[i][j-1]);
```



Original space (i, j)

- **Dependences**:
  1. $\{[i,j] \to [i+1,j] \mid 1 \le i \le N-2, 0 \le j \le N-1\}$ — **(1,0)**
  2. $\{[i,j] \to [i,j+1] \mid 1 \le i \le N-1, 0 \le j \le N-2\}$ — **(0,1)**

Domains, Dependences, and Schedules

```
for (i = 1; i <= N - 1; i++)
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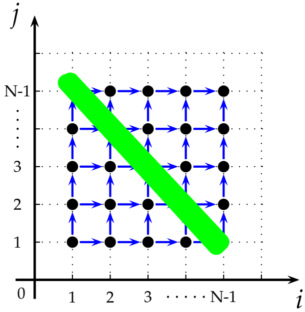

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DOMAINS, DEPENDENCES, AND SCHEDULES

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for (i = 1; i <= N - 1; i++)
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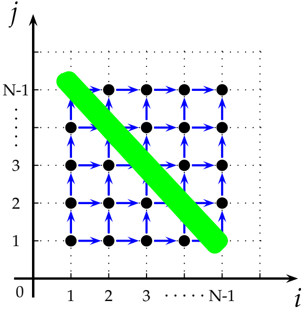
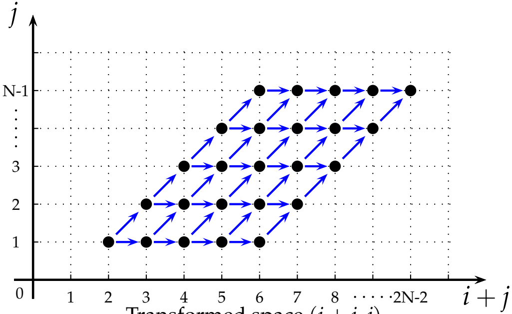


Original space (i, j)

```
for (t1=2;t1<=2*N-2;t1++) {
 #pragma omp parallel for private(lbv,ubv)
  for (t2 = max(1,t1-N+1); t2 <= min(N-1,t1-1); t2++) {
    a[(t1-t2)][t2] = a[(t1-t2) - 1][t2] + a[(t1-t2)][t2 - 1];
  }
}
```



Transformed space $(i + j, j)$

- **Schedule**: $T(i, j) = (i + j, j)$ (a multi-dimensional timestamp)
  - Dependences: (1,0) and (0,1) now become (1,0) and (1,1) resp.
  - Inner loop is now parallel

Domains, Dependences, and Schedules

```
for (i = 1; i <= N - 1; i++)
  for (j = 1; j <= N - 1; j++)
    A[i][j] = f(A[i-1][j], A[i][j-1]);
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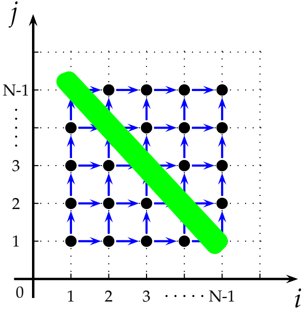

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    a[(t1-t2)][t2] = a[(t1-t2) - 1][t2] + a[(t1-t2)][t2 - 1];
  }
}
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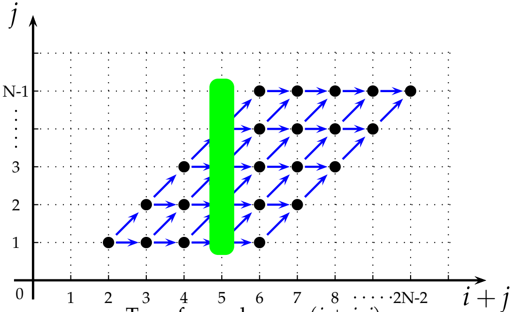

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Outline

Affine functions

- Affine for functions is linear + constant
  - Addition of identifiers, multiplication with a constant, floordiv, mod, ceildiv with respect to a positive constant
- Examples of affine functions of i, j:
  $i + j$, $2i - j$, $i + 1$, $2i + 5$,
  $i/128 + 1$, $i\%8$, $(i + j)/8$,
  $((d0 * 9216 + d1 * 128) \text{ mod } 294912) \text{ floordiv } 147456$
- Not affine: ij, i/j, j/N, $i^2 + j^2$, $a[j]$

Polyhedral Notions in MLIR

- IR structures
  - Affine maps
  - Integer sets
- Operations
  1. affine.for
  2. affine.if
  3. affine.graybox (still a proposal)
  4. affine.apply

Polyhedral Notions in MLIR

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Affine Maps in MLIR

- An affine map maps zero or more identifiers to one or more result affine expressions

$$
\begin{aligned}
\#map1 &= (d0) \rightarrow ((d0 \text{ floordiv } 4) \text{ mod } 2)\\
\#map2 &= (d0) \rightarrow (d0 - 4)\\
\#map3 &= (d0) \rightarrow (d0 + 4)\\
\#map4 &= (d0, d1) \rightarrow (d0 * 16 - d1 + 15)\\
\#map5 &= (d0, d1, d2, d3) \rightarrow (d2 - d0 * 16, d3 - d1 * 16)
\end{aligned}
$$

- Why affine maps? What can they express?
  - Loop IV mappings for nearly every useful loop transformation, data layout transformations, placement functions / processor mappings / distributions: block, cyclic, block-cyclic, multi-dimensional array subscripts, loop bound expressions, conditionals

Where are Affine Maps Used in MLIR?

1. IV remappings: to map old IVs to new IVs

$$
\begin{array}{ll}
(i, j) & \text{Identity} \\
(j, i) & \text{Interchange} \\
(i, i+j) & \text{Skew j} \\
(2i, j) & \text{Scale i by two} \\
(i, j+1) & \text{Shift j} \\
\left(\left\lfloor \frac{i}{32} \right\rfloor, \left\lfloor \frac{j}{32} \right\rfloor, i, j\right) & \text{Tile (rectangular)} \\
\ldots &
\end{array}
$$

2. Loop bounds
3. Memref access subscripts
4. As an attribute for any instruction:

```
#map = (d0) -> (2*d0 - 1)

affine.for %i1 = 0 to #map(%N) {
  affine.for %i2 = 0 to 3 {
    %v1 = affine.load %0[%i1 + %i2] : memref<100xf32>
    "op1"(%v1) : (f32) -> ()
  }
}
%v = "op"(%s, %t) {map: (d0, d1) -> (d1, d0)} : (f32) -> (f32)
```

Integer Sets in MLIR

- Affine expressions on the LHS that are $\geq$ or $= 0$
- Can be used to model several things besides *affine.if*

```
#set0 = (i)[N, M] : (i >= 0, -i + N >= 0, N - 5 == 0, -i + M + 1 >= 0)
```

AFFINE.FOR

- Uses affine maps for lower and upper bounds
- SSA values bind to dimensions and symbols of the maps

```
#map6 = (d0) -> (480, d0 * -480 + 2048)
#map7 = (d0) -> (d0 * 60)
#map8 = (d0) -> (696, d0 * 60 + 60)

  affine.for %arg3 = 0 to 5 {
   affine.for %arg4 = 0 to 12 {
    affine.for %arg5 = 0 to 128 {
     affine.for %arg6 = #map7(%arg4) to min #map8(%arg4) {
      affine.for %arg7 = 0 to min #map6(%arg3) {
       affine.for %arg8 = 0 to 16 {
        affine.for %arg9 = 0 to 3 {
         %0 = affine.load %arg0[%arg6 * 3 + %arg9, %arg3 * 480 + %arg7] : memref<2088x2048xf64>
         %1 = affine.load %arg1[%arg3 * 480 + %arg7, %arg5 * 16 + %arg8] : memref<2048x2048xf64>
         %2 = affine.load %arg2[%arg6 * 3 + %arg9, %arg5 * 16 + %arg8] : memref<2088x2048xf64>
         %3 = mulf %0, %1 : f64
         %4 = addf %3, %2 : f64
         affine.store %4, %arg2[%arg6 * 3 + %arg9, %arg5 * 16 + %arg8] : memref<2088x2048xf64>
        }
       }
      }
     }
    }
   }
  }
```

AFFINE.IF

- Uses an integer set
- SSA values bind to dimensions and symbols of the integer set

```
affine.if (d0, d1) : (d1 - d0 >= 0) (%arg0, %arg0) {
 %cf10 = addf %cf9, %cf9 : f32
}
```

What about non-affine?

- What about non-affine?

- Control flow, multi-dimensional array subscripts, loop bounds
- Things that change with loop IVs, things that are constant but unknown (symbols/parameters in polyhedral literature), and things that are known constants
- There are restrictions on what can be used as “symbols” or “parameters” for polyhedral purposes.

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Affine GrayBox

- Grayboxes introduce a new polyhedral scope / symbol context
- Allow modeling "non-affine" control flow / subscripts / bounds maximally via affine constructs without outlining functions

```
for (i = 0; i < N; i++)
  for (j = 0; j < N; j++)
    // Non-affine loop bound for k loop
    for (k = 0; k < pow(2, j); k++)
       for (l = 0; l < N; l++)
         // block loop body
        ...
```

```
%c2 = constant 2 : index
affine.for %i = 0 to %n {
  affine.for %j = 0 to %n {
    affine.graybox [] = () {
      %pow = call @powi(%c2, %j)
      affine.for %k = 0 to %pow {
        affine.for %l = 0 to %n {
          ...
        }
      }
      return
    } // graybox end
  } // %j
} // %i
```

Outline

Types Relevant for Dense Matrices / Tensors

1. *tensor* A value that is a multi-dimensional array of elemental values

```
%d = "tf.Add"(%e, %f)
: (tensor<?x42x?xf32>,tensor<?x42x?xf32>) -> tensor<?x42x?xf32>
```

2. *memref* A buffer in memory or a view on a buffer, has a layout map, memory space qualifier, symbols bound to its dynamic dimensions

```
%N = affine.apply (d0) -> (8 * (d0 ceildiv 8)) (%S)
%M = affine.apply (d0) -> (2 * d0) (%N)
#tmap = (d0, d1) -> (d1 floordiv 32, d0 floordiv 128, d1 mod 32, d0 mod
128)
%A = alloc() : memref<1024x64xf32, #tmap, /*hbm=*/0>
%B = alloc(%M, %N)[%x, %y] : memref<?x?xf32, #tmap, /*scratchpad=*/1>

#shift = (d0, d1)[s0, s1] -> (d0 + s0, d1 + s1)
%C = alloc(%M, %M)[%x, %y] : memref<?x?xf32, #shift, /*scratchpad=*/1>
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OUTLINE

State-of-the-Art Deep Learning Systems: Current Landscape

- Primarily driven by hand-optimized highly tuned libraries (manual or semi-automatic at most)
- Expert/Ninja programmers
- Not a scalable approach! — bleeds resources, not modular, too much repetition

Modular and Systematically Optimized BLAS

- **Van Zee and Van de Geijn 2015** work on BLIS/FLAME has shown how to modularize/structure such Ninja implementations (Goto's/OpenBLAS) for auto-generation
- **Low et al. 2015** shows how parameters for such systematic implementations could be derived completely analytically!
- Close to absolute machine peak performance achievable in a structured/more productive way (for Intel / AMD multicores)!
- MLIR and its infrastructure could take this approach even further
- Turn a ninja / esoteric art into a more productive, automatable, and scalable approach

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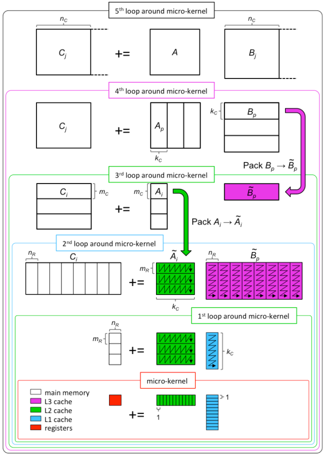
OPENBLAS/BLIS APPROACH TO TILING



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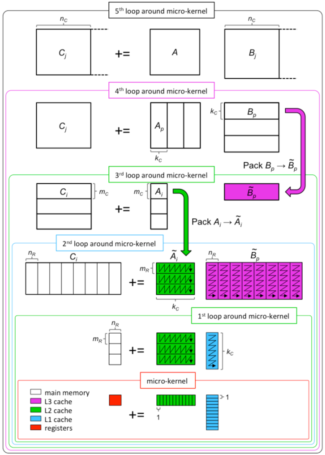
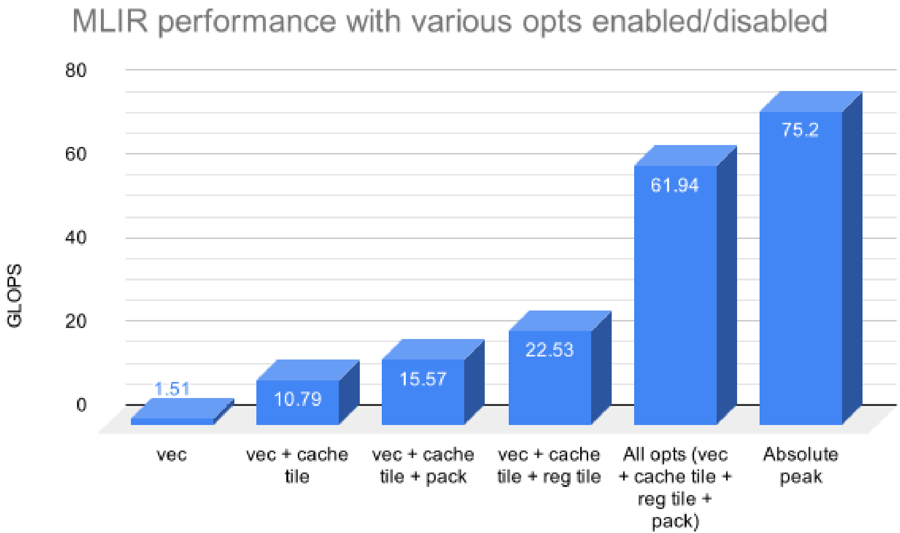


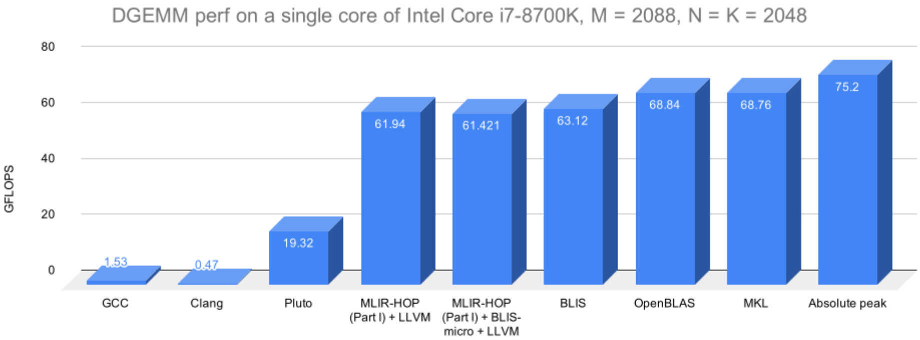
Schedule:

$$(i, j, k) \rightarrow \left(\frac{j}{N_C}, \frac{k}{K_C}, \frac{i}{M_C}, \quad \frac{j}{N_R}, \frac{i}{M_R}, k, \quad j \,\%\, N_R, i \,\%\, M_R \right)$$

RECREATING DGEMM IN MLIR

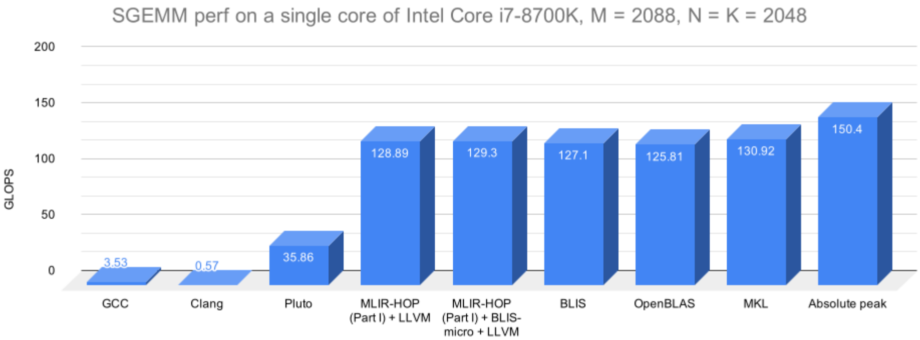


Recreating DGEMM in MLIR



- **Within 9% of MKL/OpenBLAS performance!**

Recreating SGEMM in MLIR



- **Within 2% of MKL/OpenBLAS performance!**

Outline

Opportunities

- Migrate and rebuild existing polyhedral infrastructure in a principled way on MLIR ⇒ greater impact / industry transfer / reuse
- Transform both iteration spaces and data spaces; better phase ordering / interaction with SSA
- Building new DSLs/programming models? Use MLIR!
- Building new ML/AI chips? Create an MLIR backend!

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Conclusions

- Need for reusable and modular common IR infrastrucutre to lower compute graphs to high-performance code
- Lowering should be **progressive** — input and output of passes/utilities should be **easy to represent and transform**
- Infrastructure for analysis and transformation should be **reused**, not replicated
- High-performance libraries and code generators should coexist, interoperate, and compose
- General-purpose and domain-specific techniques can coexist on the same IR infrastructure

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Interested?

1. **Contribute to MLIR (part of LLVM now): https://github.com/llvm-project/llvm**
2. **Several collaboration opportunities with academia and industry!**
3. **Several employment opportunities!**

4. **Pointers**
   4.1 **MLIR documentation: https://mlir.llvm.org**
   4.2 **My branches: https://github.com/llvm-project/bondhugula/**