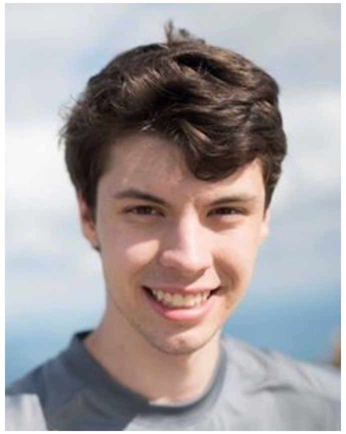
Polygeist: Raising C to Polyhedral MLIR



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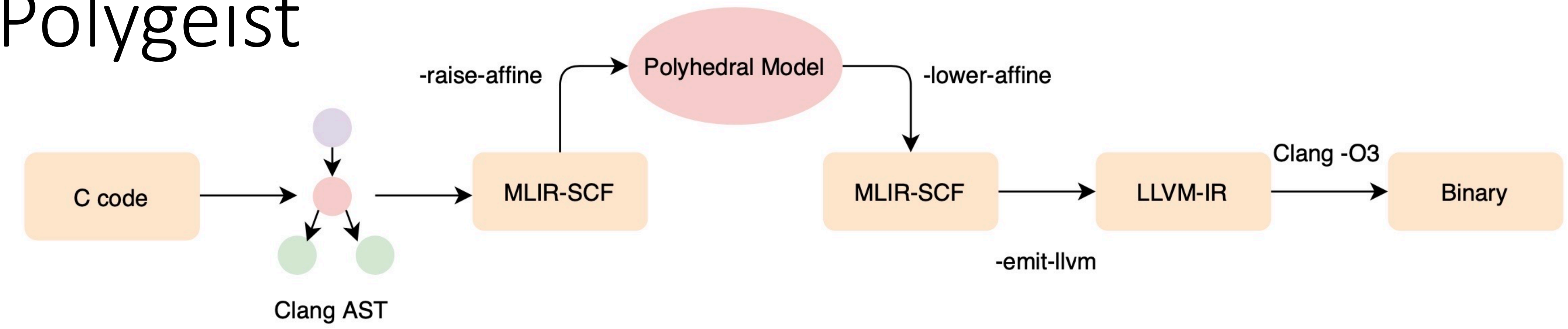
Motivation

- The compiler research has recently been enamored by the MLIR framework, whose first-class polyhedral representation may provide benefits on a variety of codes
- We can fully leverage decades of polyhedral research by connecting MLIR with existing polyhedral tools.
- Without MLIR-versions of standard polyhedral benchmarks, one cannot perform a fair assessment
- Goal of this work is to provide a fair baseline for subsequent work AND explore the potential of polyhedral optimizations that require both high level and low level information

Polygeist

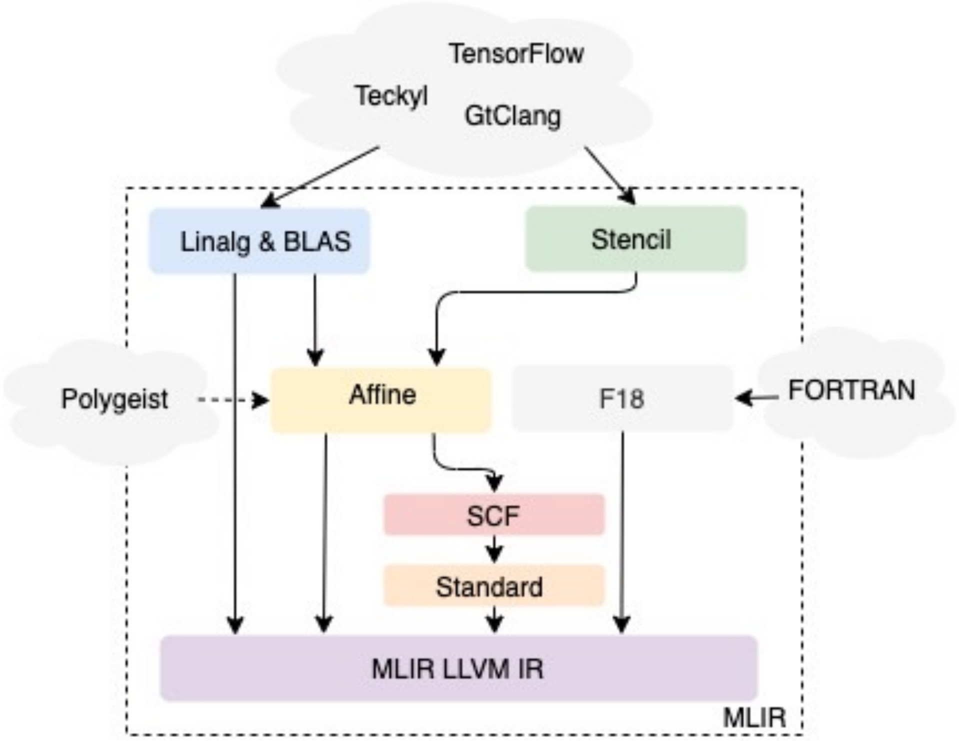


A platform for polyhedral transformations within MLIR

- Generic C or C++ frontend that generates "standard" MLIR
- Raising transformations for transforming "standard" MLIR to polyhedral MLIR (Affine)
- Embedding of existing polyhedral tools (Pluto, CLooG) into MLIR
- Novel transformations (statement splitting, reduction detection) that rely on high-level compiler representation
- Polyhedral benchmarks for MLIR based off of Polybench
- End-to-end evaluation on standard polyhedral benchmarks

The MLIR Framework

- A toolkit for representing and transforming "code"
  - Modular and extensible via dialects (namespaces of operations/types and attributes)
  - Non-opinionated – choose the level of abstraction that is right for you
  - State-of-the-art SSA-based compiler technology



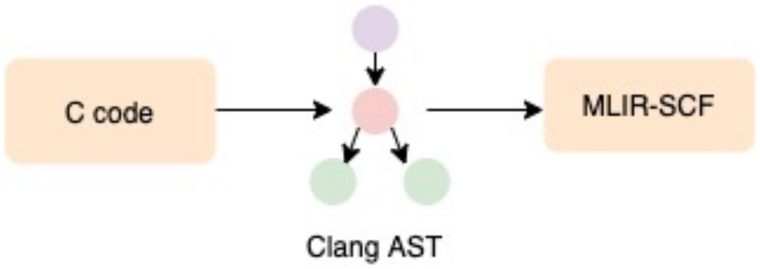

```
%result = "dialect.operation"(%operand, %operand)
          {attribute = #dialect<"value">} ({
^basic_block(%block_argument: !dialect.type):
  "another.operation"() : () -> ()
}) : (!dialect.type) -> !dialect.result_type
```

The Affine dialect

- Represent SCoP with polyhedral-friendly loops and conditions
- Core Affine representation
  - Symbols - parameters
  - Dimensions - symbol extension that accepts induction variables
  - Maps - multi-dimensional function of symbols and dimensions
  - Sets - integer tuples constrained by a conjunction

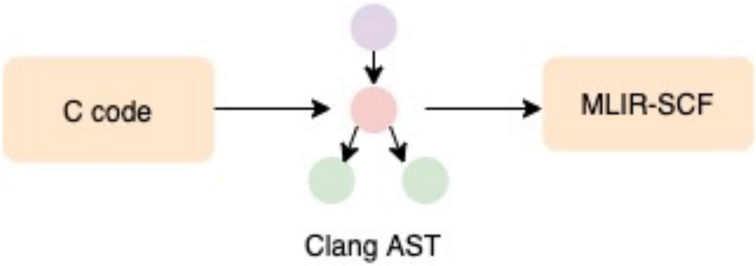
```
%c0 = constant 0 : index
%0 = dim %A, %c0 : memref<?xf32>
%1 = dim %B, %c0 : memref<?xf32>
affine.for %i = 0 to affine_map<()[s0] -> (s0)>()[%0] {
  affine.for %j = 0 to affine_map<()[s0] -> (s0)>()[%1] {
    %2 = affine.load %A[%i] : memref<?xf32>
    %3 = affine.load %B[%j] : memref<?xf32>
    %4 = mulf %2, %3 : f32
    %5 = affine.load %C[%i + %j] : memref<?xf32>
    %6 = addf %4, %5 : f32
    affine.store %6, %C[%i + %j] : memref<?xf32>
  }
}
```

Polygeist Frontend



- Built a generic C or C++ frontend for MLIR, based off of Clang
- C control flow directly lowered to MLIR for, if, etc..
- Variables and arrays represented by MLIR `memref` (memory reference) construct
- Loops within a scop are assumed to be affine, with other loops raised if proven to be affine

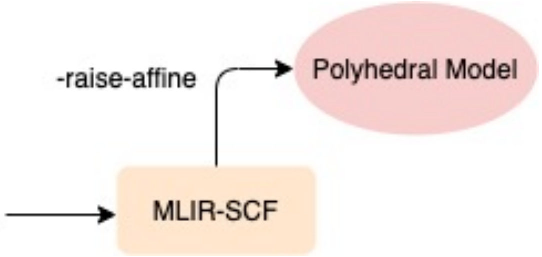
Polygeist Frontend




```
void set(int *arr, int val) {
  #pragma scop
  for(int i=0; i<10; i++){
    arr[2*i] = val;
  }
  #pragma endscop
}
```

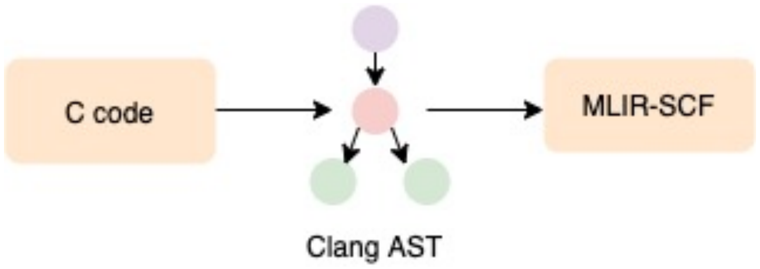
```
func @set(%arg0: memref<?xi32>, %arg1: i32) {
  %c0 = constant 0 : index
  %0 = alloca() : memref<1xmemref<?xi32>>
  store %arg0, %0[%c0] : memref<1xmemref<?xi32>>
  %1 = alloca() : memref<1xi32>
  store %arg1, %1[%c0] : memref<1xi32>
  %c0_i32 = constant 0 : i32
  %c2_i32 = constant 2 : i32
  %c10_i32 = constant 10 : i32
  %2 = index_cast %c10_i32 : i32 to index
  scf.for %arg2 = %c0_i32 to %2 {
    %3 = index_cast %arg2 : index to i32
    %4 = alloca() : memref<1xi32>
    store %3, %4[%c0] : memref<1xi32>
    %5 = load %0[%c0] : memref<1xmemref<?xi32>>
    %6 = load %4[%c0] : memref<1xi32>
    %7 = muli %c2_i32, %6 : i32
    %8 = index_cast %7 : i32 to index
    %9 = load %1[%c0] : memref<1xi32>
    store %9, %5[%8] : memref<?xi32>
  }
  return
}
```

Polygeist Raising



- Directly lowered constructs are not valid polyhedral programs
- Local variables eliminated, if possible, by new MLIR mem2reg pass
- Loads and stores are raised to affine loads, if possible
  - Detect if index calculation is a valid affine expression
  - Progressively fold index calculation into an affine operation
- if statements are changed to affine if their condition can be raised
- Loops canonicalized and raised if legal (while => for, scf.for => affine.for, etc)

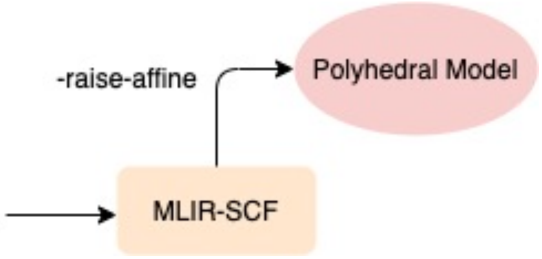
Polygeist Raising




```
func @set(%arg0: memref<?xi32>, %arg1: i32) {
    %c0 = constant 0 : index
    %0 = alloca() : memref<1xmemref<?xi32>>
    store %arg0, %0[%c0] : memref<1xmemref<?xi32>>
    %1 = alloca() : memref<1xi32>
    store %arg1, %1[%c0] : memref<1xi32>
    %c0_i32 = constant 0 : i32
    %c10_i32 = constant 10 : i32
    %2 = index_cast %c10_i32 : i32 to index
    scf.for %arg2 = %c0_i32 to %2 {
      %3 = index_cast %arg2 : index to i32
      %4 = alloca() : memref<1xi32>
      store %3, %4[%c0] : memref<1xi32>
      %5 = load %0[%c0] : memref<1xmemref<?xi32>>
      %c2_i32 = constant 2 : i32
      %6 = load %4[%c0] : memref<1xi32>
      %7 = muli %c2_i32, %6 : i32
      %8 = index_cast %7 : i32 to index
      %9 = load %1[%c0] : memref<1xi32>
      store %9, %5[%8] : memref<?xi32>
    }
    return
  }
```

```
func @set(%arg0: memref<?xi32>, %arg1: i32) {
   affine.for %arg2 = 0 to 10 {
     affine.store %arg1, %arg0[%arg2 * 2]
       : memref<?xi32>
   }
   return
 }
```

Polygeist Raising



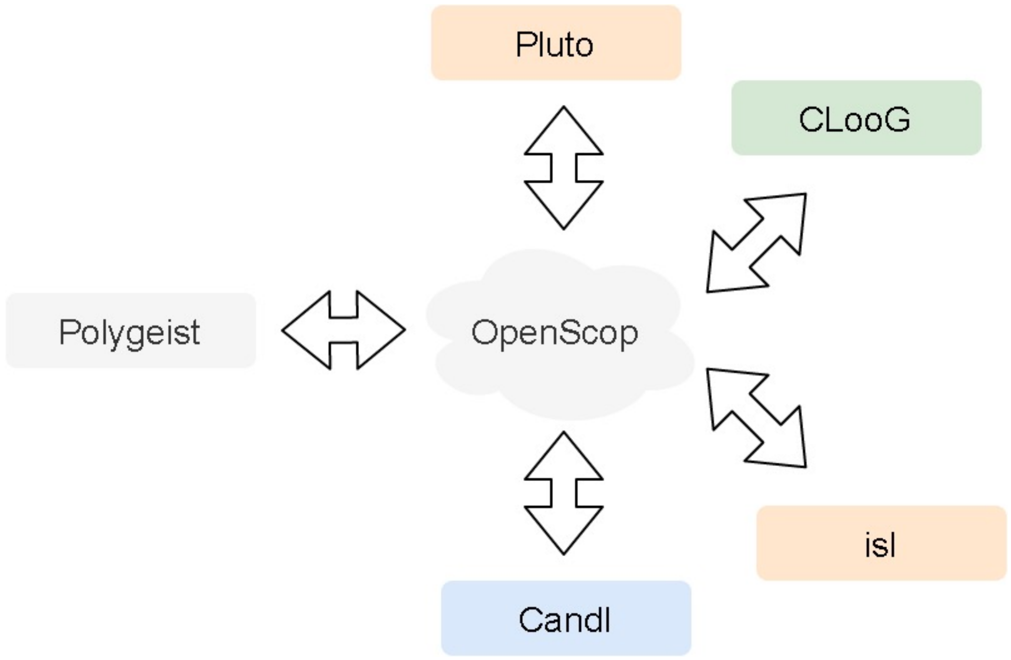
- Select statements must be represented by a C ternary operator
  - C ternaries have lazy-evaluation semantics which are replicated in the generated MLIR
  - Mem2Reg and code motion attempt to remove unnecessary loads within if's to generate a valid select.

```
prefixMax[i] = (prefixMax[i-1] >= data[i])
                ? prefixMax[i-1] : data[i];
```

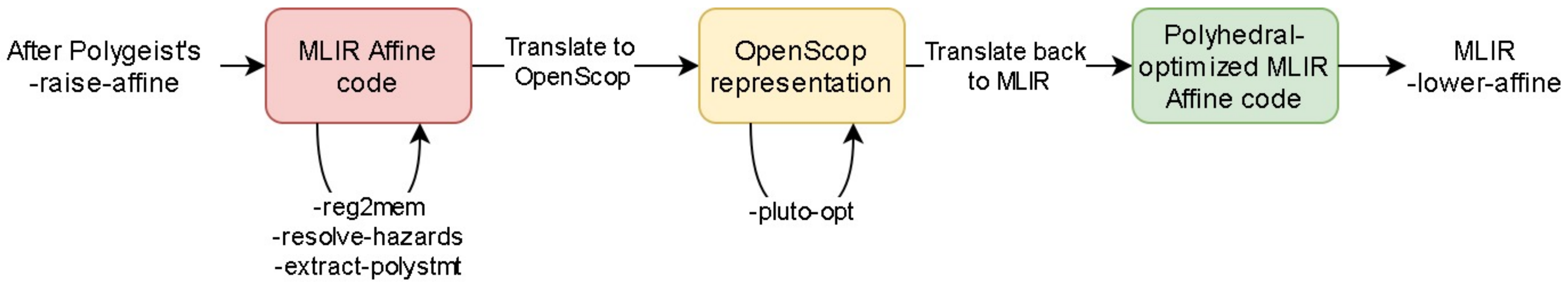
```
%0 = index_cast %arg2 : i32 to index
%1 = subi %0, %c1 : index
%2 = load %arg0[%1] : memref<?xi32>
%3 = load %arg1[%0] : memref<?xi32>
%4 = cmpi "sgt", %2, %3 : i32
%5 = scf.if %4 -> (i32) {
  %6 = load %arg0[%1] : memref<?xi32>
  scf.yield %6 : i32
} else {
  %6 = load %arg1[%0] : memref<?xi32>
  scf.yield %6 : i32
}
store %5, %arg0[%0] : memref<?xi32>
```

Connecting MLIR to Polyhedral Tools

- Polygeist can obtain polyhedral representation in MLIR Affine
- But it is difficult to leverage existing polyhedral tools
- OpenScop is the interchangeable format among polyhedral tools
- How to translate between MLIR code and OpenScop representation?



Polyhedral Optimization Pipeline

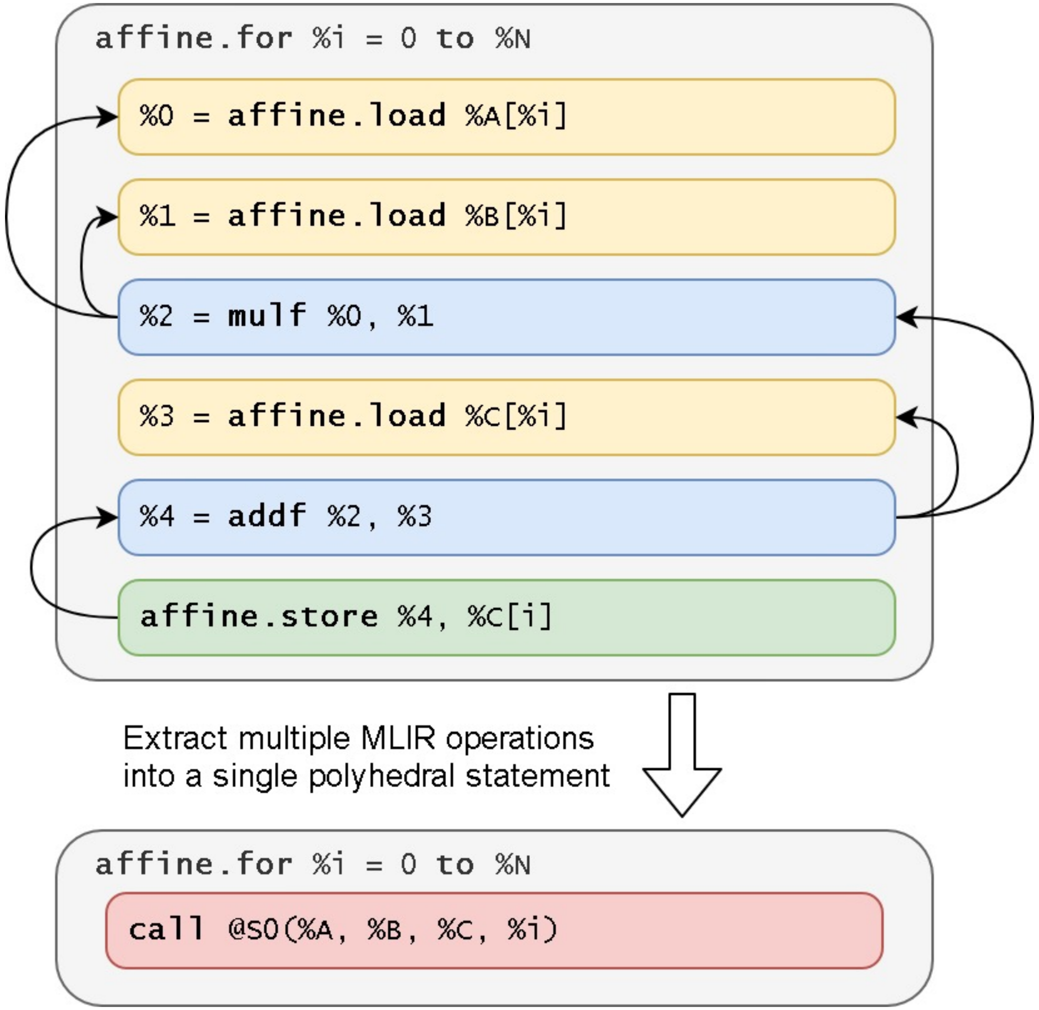


Polyhedral Statement

- OpenScop expects C-like statements:

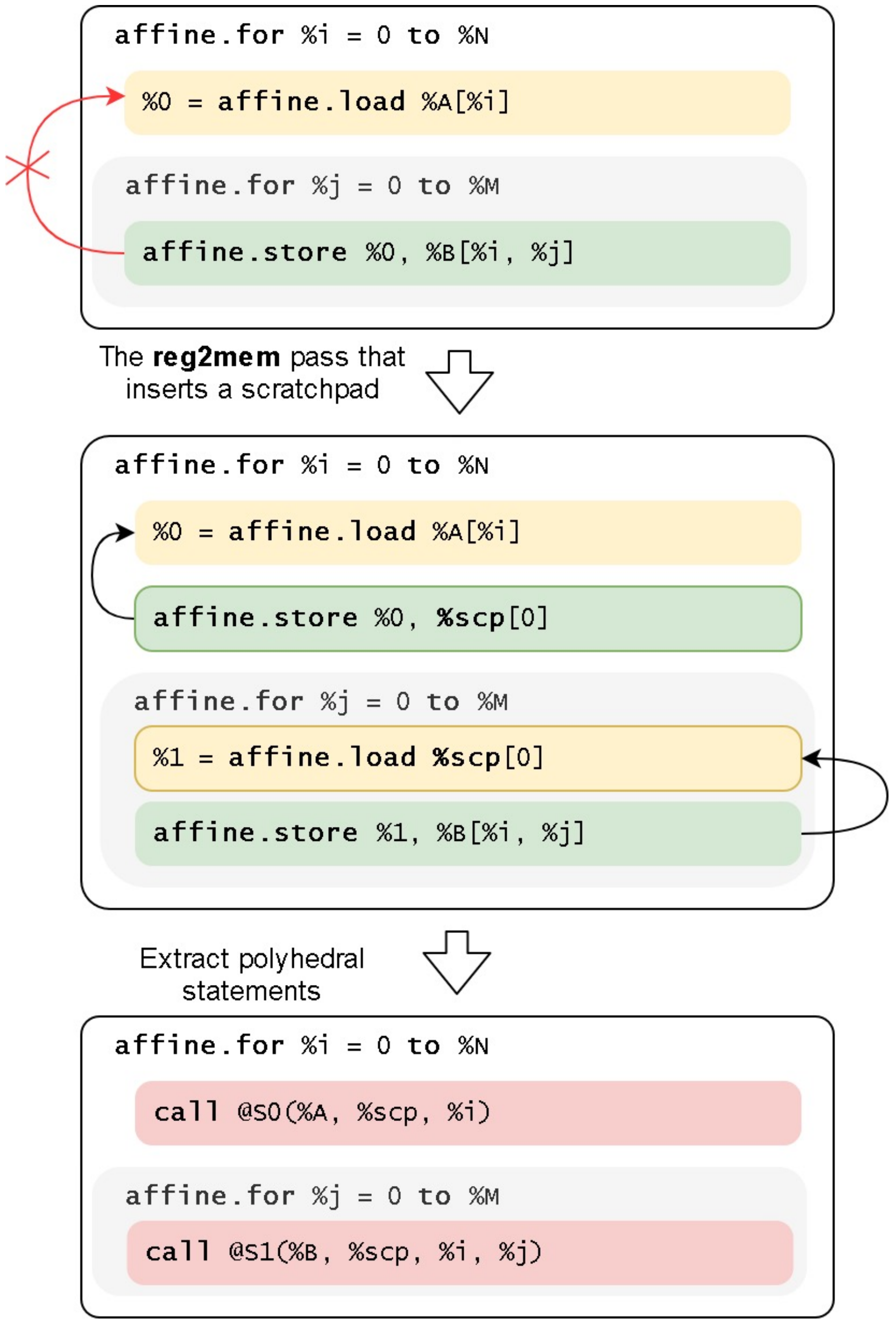
```
C[i][j] += A[i][k] * B[k][j]
```

- MLIR is lower level and a store instruction alone does not specify how to compute the stored operand
- 1 OpenScop statement may correspond to many MLIR operations
- To match C-like statements:
  - Extract 1 MLIR memory write
  - Traverse SSA use-def chains
  - Continue until all operations are loads or symbols



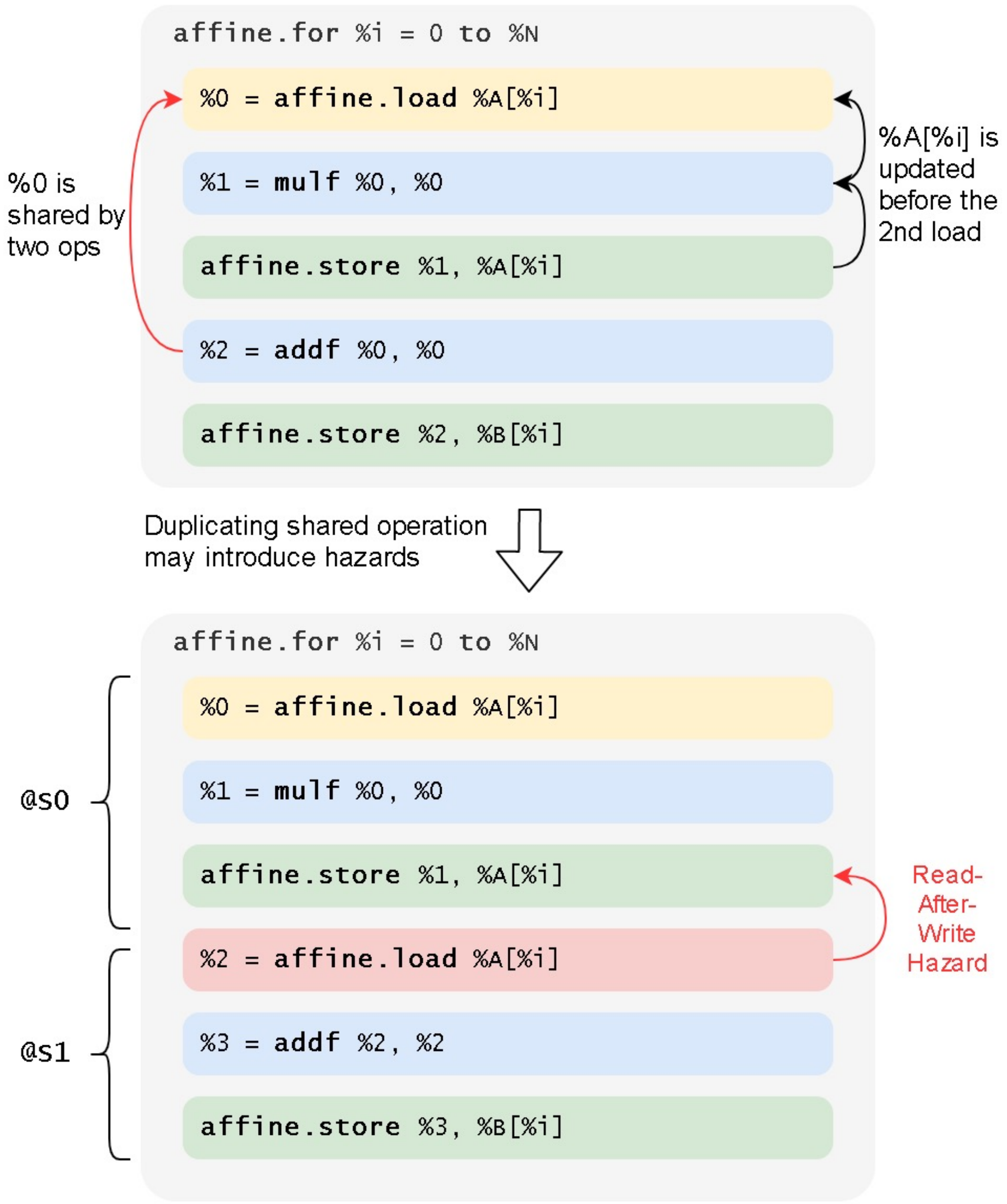
Region-Spanning Problem

- A use-def chain may span multiple loops (regions).
  - e.g., A load op defines a register used by other ops in inner loops.
- Statement nesting in loops is ambiguous
- Difficult to reconstruct when converting back to MLIR
- Reg2mem pass: insert a scratchpad for each use-def across regions



Avoid RAW Hazard

- The RAW hazard problem:
  - A load op is duplicated for use in multiple statements
  - Intermediate writes may clobber
  - After extraction, later statements may load wrong values
- Simplified value analysis to detect
- Insert scratchpads



Outlining

- We outline statements into functions
- Opaque calls with known memory footprints
- Lift local stack allocations and symbol definitions

```
func @S0(%A: memref<?xf32>) {
  %c0 = constant 0 : index
  %s0 = dim %A, %c0 : index
  %1 = affine.load %A[0]
  affine.store %1, %A[symbol(%s0) - 1]
  return
}
```

Lift local symbols to the function interface

```
func @S0(%A: memref<?xf32>, %s0: index ) {
  %0 = affine.load %A[0]
  affine.store %0, %A[%s0 - 1]
  return
}
```

Statement Splitting

- The previous slides describe how Polygeist attempts to reconstruct statements similar to the original C input.
- We can instead form statements out of any subset of operations, assuming dependencies hold.
- The ability to split statements gives the schedular additional flexibility and choose different schedules for different parts of the same program.
- This is difficult to do at a source level as it requires reinterpreting C/C++ semantics, and also difficult in low-level IR’s that lack loops and multidimensional indexing

Translate to OpenScop

- First pre-process MLIR Affine code by previous passes
- For each extracted polyhedral statement:
  - Domain: get constraints from affine.for/if
  - Initial Schedule: derive from region nesting and operation order
  - Access: extract from affine load/stores
- Store symbols in OpenScop extensions

Translate to OpenScop

```
affine.for %i = 0 to %N
  affine.for %j = 0 to %N
    call @S0(%A, %i, %j )
```

```
func @S0(%A: memref<?x?xf32>, %i: index,
         %j: index) {
  %0 = affine.load %A[%i, %j]
  %1 = mulf %0, %0
  affine.store %1, %A[%i, %j]
  return
}
```

Domain

```
# e/i | %i    %j | %N   | 1
   1     1    0     0     0     ## %i >= 0
   1    -1    0     1    -1     ## -%i+%N-1 >= 0
   1     0    1     0     0     ## %j >= 0
   1     0   -1     1    -1     ## -%j+%N-1 >= 0
```

Scattering

```
# e/i| s1   s2   s3   s4   s5   |%i   %j  | %N  | 1
  0   -1    0    0    0    0    0    0    0    0
  0    0   -1    0    0    0    1    0    0    0
  0    0    0   -1    0    0    0    0    0    0
  0    0    0    0   -1    0    0    1    0    0
  0    0    0    0    0   -1    0    0    0    0
```

READ/WRITE Accesses

```
# e/i| Arr  [1]  [2] |%i   %j  | %N  | 1
  0   -1    0    0    0    0    0    0     ## %A
  0    0   -1    0    1    0    0    0     ## %i
  0    0    0   -1    0    1    0    0     ## %j
```

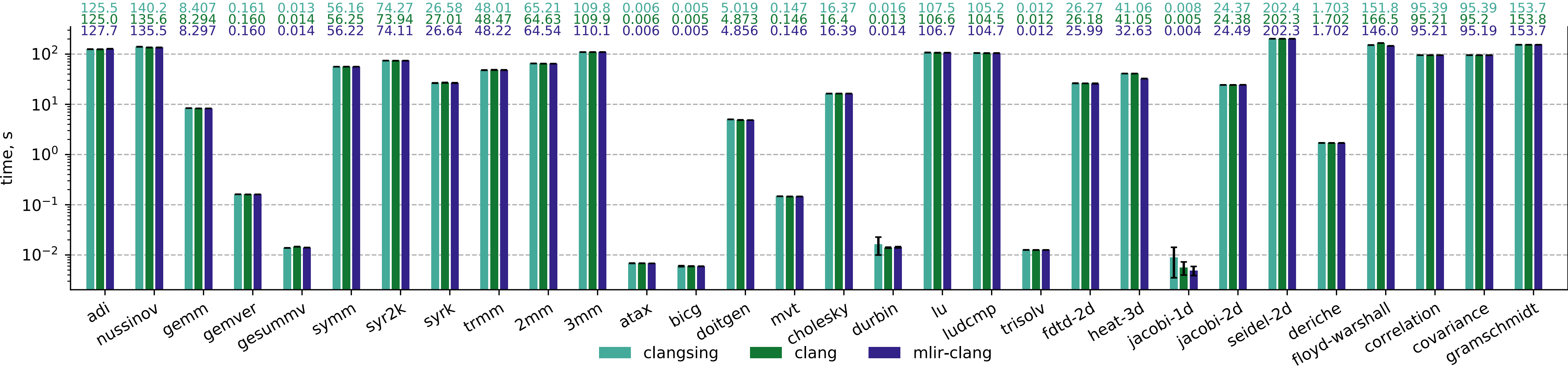
Regenerate MLIR Code

- Obtain a CLooG AST from an optimized OpenScop representation
- Regenerate MLIR code by traversing AST
- OpenScop symbols will be translated to MLIR values or operations based on a maintained symbol table.

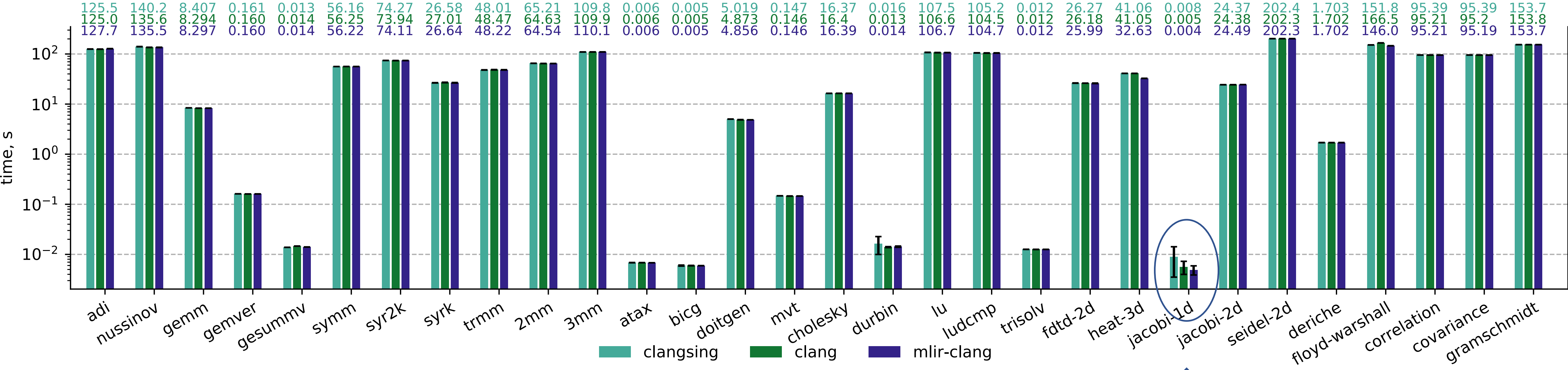
Evaluation

- Compare Polygeist frontend with Clang
- Compare Polygeist polyhedral optimization with native Pluto
- Novel optimizations

Serial Non-Polyhedral Comparison



Serial Non-Polyhedral Comparison



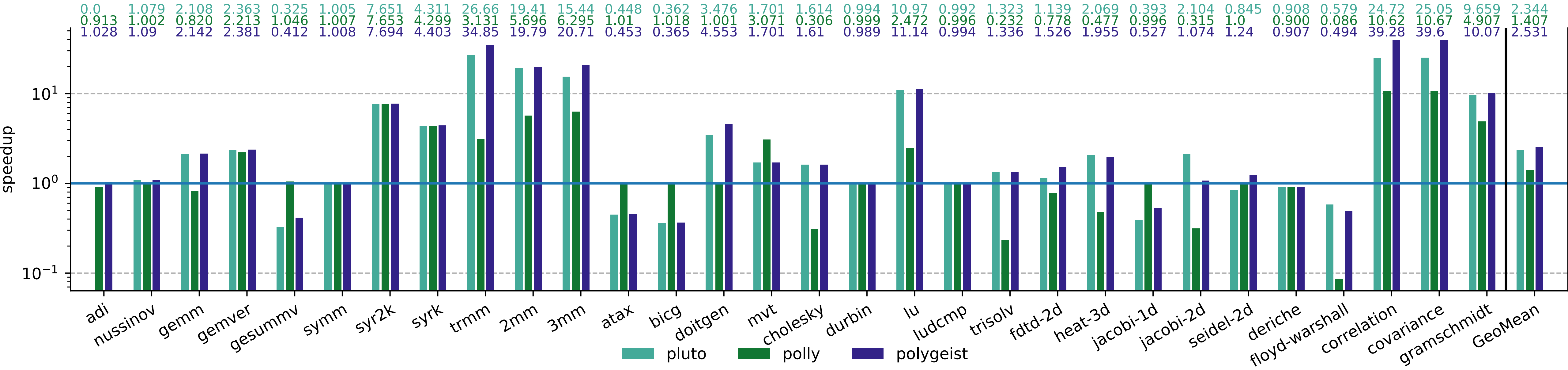
Frontend within 0.32% of "standard" frontend

Remaining gap attributed to small tests where minor assembly differences matter

Frontend Performance Differences

- 8% performance boost on Floyd-Warshall occurs if Polygeist generates a single MLIR module for both benchmarking and timing code by default
- MLIR doesn't properly generate LLVM datalayout, preventing vectorization for MLIR-generated code (patched in our lowering)
- Different choice of allocation function can make a 30% impact on some tests (adi)
- LLVM strength-reduction is fragile and sometimes misses reversed loop induction variable (remaining gap in adi)

Sequential Polyhedral Comparison



Polygeist: 2.53x speedup

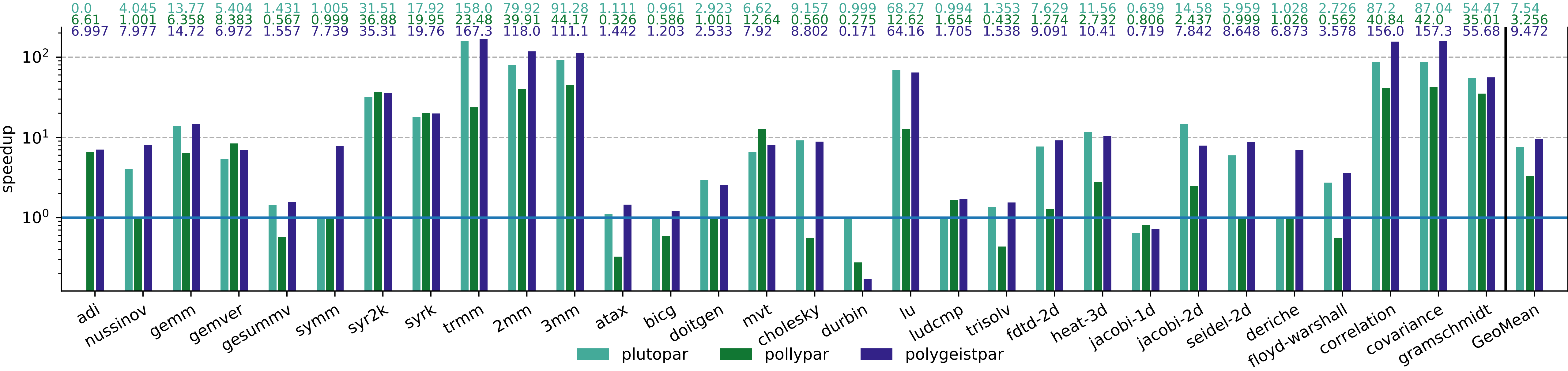
Pluto: 2.34x speedup

Polly: 1.41x speedup

Polyhedral Performance Differences

- Polly differs from other two as it uses a different scheduler
- Even when using the same scheduler, Polygeist can select a different statement set and thus schedule coming from partially optimized SSA rather than the original C.
- Pluto executes significantly more (~10^11) more integer instructions on seidel-2d than Polygeist, which is ~59s at 3GHz, accounting for the gap. Can be caused by different integer optimization and the use of a proper machine type/bound simplification.
- For jacobi-2d, Polygeist performs worse, stopping earlier when simplifying (75 statement copies in 40 branches), whereas Clang by default takes longer to process this but has better end vectorization.

Parallel Polyhedral Comparison



Polygeist: 9.47x speedup

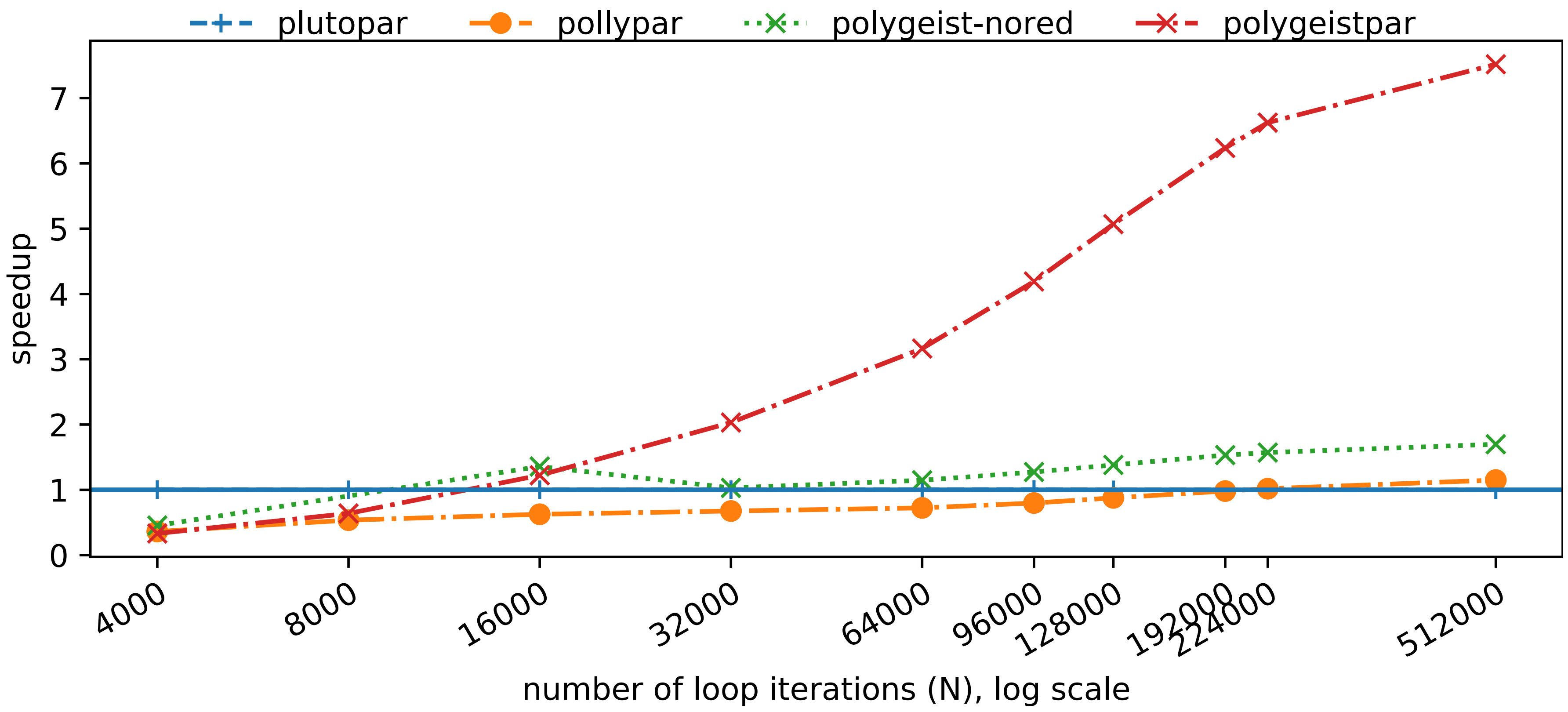
Pluto: 7.54x speedup

Polly: 3.26x speedup

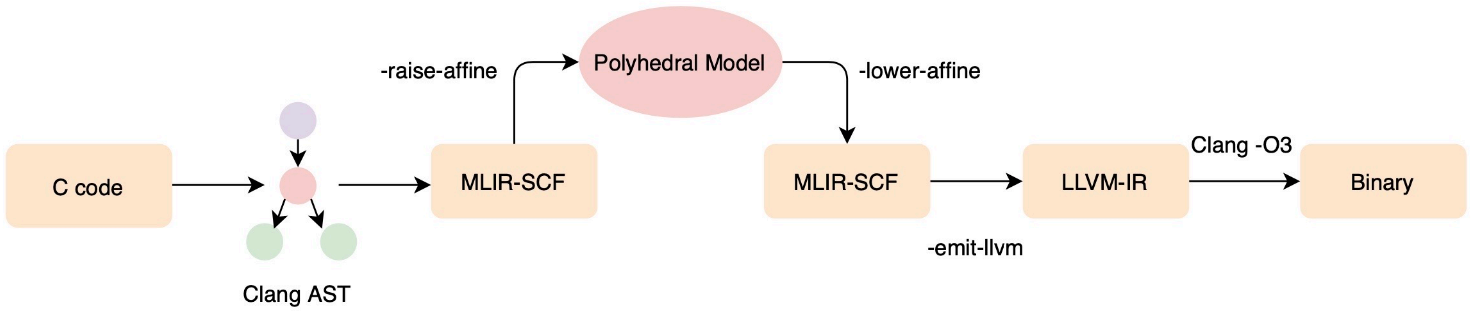
Parallel Performance Differences

- Same scheduling differences as sequential (Cholesky and LU are better on Pluto/Polygeist than Polly; Gemver and MVT are better on Polly)
- Ludcmp and syr(2)k benefit from SSA optimizations
- Polygeist is only framework that can parallelize deriche (6.9x) and symm (7.7x) by analyzing and removing the loop-carried dependency
- Polygeist identifies a parallel reduction within gramschmidt (56x Polygeist, 54x Pluto, 34x Polly) and durbin (6x slowdown as few iterations)

Parallel Reduction Detection (durbin)

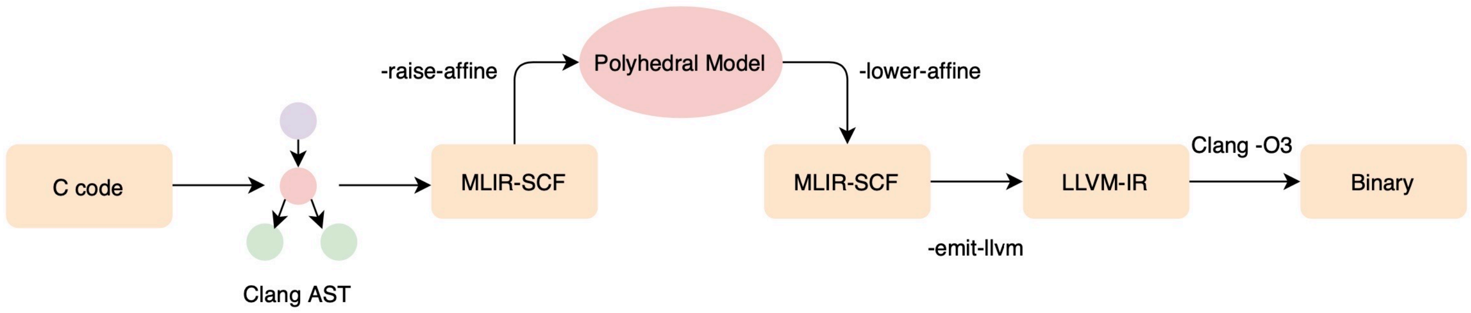


Conclusion



- Polygeist provides tools to fairly compare MLIR-based polyhedral flows with prior Polyhedral tools
  - C or C++ frontend for (Affine) MLIR
  - Integration of existing polyhedral tools for transforming MLIR
  - End-to-end comparison using existing Polyhedral benchmarks (Polybench)
- Polygeist outperforms existing Polyhedral optimizers for both serial and parallel code generation
- Polygeist provides an easy platform to introduce novel polyhedral optimizations (statement splitting, reduction) that are difficult to perform on existing representations

Future Work



- GPU optimization and GPU <-> CPU
- Embedded DSL / C-style semantics for directly generating MLIR Ops
- LLVM Incubator Project

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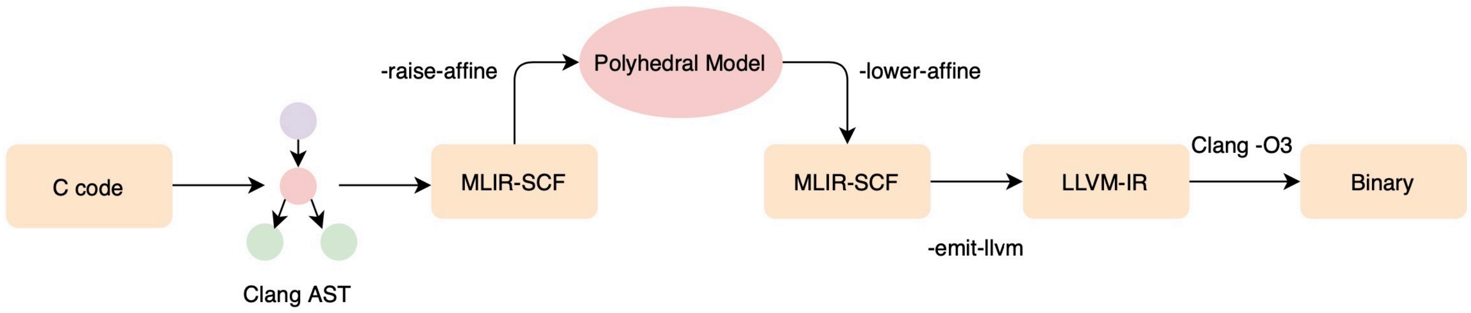
Conclusion



- Polygeist provides tools to fairly compare MLIR-based polyhedral flows with prior Polyhedral tools
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- Polygeist provides an easy platform to introduce novel polyhedral optimizations (statement splitting, reduction) that are difficult to perform on existing representations

Backup Slides

```
func @set(%arg0: memref<?xi32>, %arg1: i32) {
   affine.for %arg2 = 0 to 10 {
     affine.store %arg1, %arg0[%arg2 * 2] : memref<?xi32>
   }
   return
 }
```

Conclusion

- Polygeist providing tools to fairly compare MLIR-based polyhedral representations with prior art in Polyhedral representations
    - C/C++ frontend for (Affine) MLIR
    - Integration of existing polyhedral tools for transforming MLIR (via OpenScop)
    - End-to-end comparison using existing Polyhedral benchmarks (Polybench)
- Polygeist enables future research on polyhedral MLIR transformations
- MLIR-based frontend differs from Clang by 1.25%
- @Ruizhe, add a good polymer conclusion