# A practical introduction to MLIR for HPC using Python

**Wash up from exercises and key takeaway points**

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# Where we are

| Time | Details | Type |
|---|---|---|
| 9:00 - 9:05 | Introduction, welcome and objectives | Presentation |
| 9:05 - 9:25 | An overview of MLIR and LLVM | Presentation |
| 9:25 - 9:55 | The xDSL framework | Presentation |
| 9:55 - 10:00 | Introduction to the hands-on activity | Presentation |
| 10:00 - 10:15 | Logging into ARCHER2 and start hands-on practical activity | Hands-on |
| 10:15 - 10:30 | Morning break | |
| 10:30 - 10:35 | Welcome back and overview of second part | Presentation |
| 10:35 - 12:10 | Continue hands-on practical activity | Hands-on |
| 12:10 - 12:20 | Wash up from practical activities, highlighting key take-away points | Presentation |
| 12:20 - 12:30 | Conclusions & next steps to continue working with the technologies | Presentation |

*We wrapped up exercise one at the start of the second part, so here we focus on exercises two and three*

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# Exercise two

- Extending our (very simple!) compiler to support loops

1. *Support in the tiny py dialect for the loop construct*
2. *Generate tiny py loop from python compiler*
3. *Support in the tiny py to standard dialects lowering transformation to then lower this appropriately*

*We print the result at the end just so the compiler does not optimise the calculation out!*

```
from python_compiler import python_compile

@python_compile
def ex_two():
    val=0.0
    add_val=88.2
    for a in range(0, 100000):
      val=val+add_val
    print(val)

ex_two()
```

*Remember, sample solutions are provided in the repository*

# Tiny py dialect support

**The name of the loop variable is a string attribute**

**The from and to loop expressions are regions**

**Body of the loop is also a region**

**If a Python string is provide we wrap it in the xDSL/MLIR StringAttr**

**Builds the operation (note how we create a region and block that contains the operations**

```
@irdl_op_definition
class Loop(IRDLOperation):
  name = "tiny_py.loop"

  variable: OpAttr[StringAttr]
  from_expr: Region
  to_expr: Region
  body: Region

  @staticmethod
  def get(variable: str | StringAttr,
          from_expr: Operation,
          to_expr: Operation,
          body: List[Operation],
          verify_op: bool = True) -> If:
        if isinstance(variable, str):
            # If variable is a string then wrap it in StringAttr
            variable=StringAttr(variable)

        res = Loop.build(attributes={"variable": variable}, regions=[Region([Block([from_expr])]),
            Region([Block([to_expr])]), Region([Block(body)])])
        if verify_op:
            # We don't verify nested operations since they might have already been verified
            res.verify(verify_nested_ops=False)
        return res
```

*This is what you needed to add, as we already provided the get method*

# Hooking this up….

```
def visit_For(self, node):
  contents=[]

  for a in node.body:
    contents.append(self.visit(a))

  expr_from=self.visit(node.iter.args[0])
  expr_to=self.visit(node.iter.args[1])

  return tiny_py.Loop.get(node.target.id,
            expr_from, expr_to, contents)
```

**The name of the loop variable is a string attribute**

```
tiny_py.module() {
  tiny_py.function() ["fn_name" = "ex_two",
        "return_var" = !empty, "args" = []] {
    ...
    tiny_py.loop() ["variable" = "a"] {
      tiny_py.constant() ["value" = 0 : !i32]
    } {
      tiny_py.constant() ["value" = 100000 : !i32]
    } {
      tiny_py.assign() ["var_name" = "val"] {
        tiny_py.binaryoperation() ["op" = "add"] {
          tiny_py.var() ["variable" = "val"]
        } {
          tiny_py.var() ["variable" = "add_val"]
        }
      }
    }
    ...
  }
}
```

**The from and to loop expressions are regions**

**Body of the loop is also a region**

# Supporting this in the lowering

- We provided most of the lowering from the tiny py loop to the standard dialects, but there were a couple of missing parts that we walked you through completing
  - The sample solutions illustrate the completion of this, which should be obvious from the instructions (let us know if not!)

- We translate into the *for* operation of the *structured control flow* (*scf*) dialect
  - There is also a *control flow* (*cf*) dialect, and this contains building blocks such as branch and conditional branch.
  - A conditional branch is driven by a 1 bit integer (e.g. a Boolean), this is often generated by the *cmpi* and *cmpf* operations (compare integer, compare float) in the *arith* dialect
  - MLIR will lower *scf* into its *cf* counterpart, but means we work with higher level constructs

# Lowering with MLIR

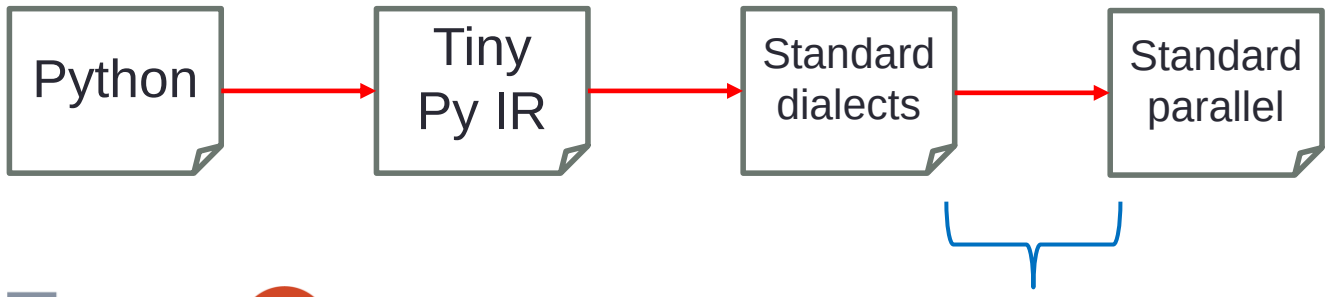
mlir-opt --pass-pipeline="builtin.module(loop-invariant-code-motion, convert-scf-to-cf, convert-cf-to-llvm{index-bitwidth=64}, convert-arith-to-llvm{index-bitwidth=64}, convert-func-to-llvm, reconcile-unrealized-casts)" ex_two.mlir

- The arguments provided to mlir-opt are quite a bit more complex than exercise one, but that's because we need to lower the loops.
  - Lowering transformation passes are in blue (see how we provide arguments to some of these)
  - Optimisation passes in red (this moves statements outside of the loop body where possible)
  - Instructions to MLIR in green (here to instruct MLIR to put in explicit operations for undertaking implicit data conversion)
- The result of this is then translated into LLVM-IR by *mlir-translate*

# Exercise three

- Parallelisation of our loops
  1. *Exploit threaded parallelism*
  2. *Vectorise our calculations*

*The user code remains unchanged, we are looking to apply an automatic transformation here to achieve these things*




```
from python_compiler import python_compile

@python_compile
def ex_three():
    val=0.0
    add_val=88.2
    for a in range(0, 100000):
      val=val+add_val
    print(val)

ex_three()
```

*Remember, sample solutions are provided in the repository*

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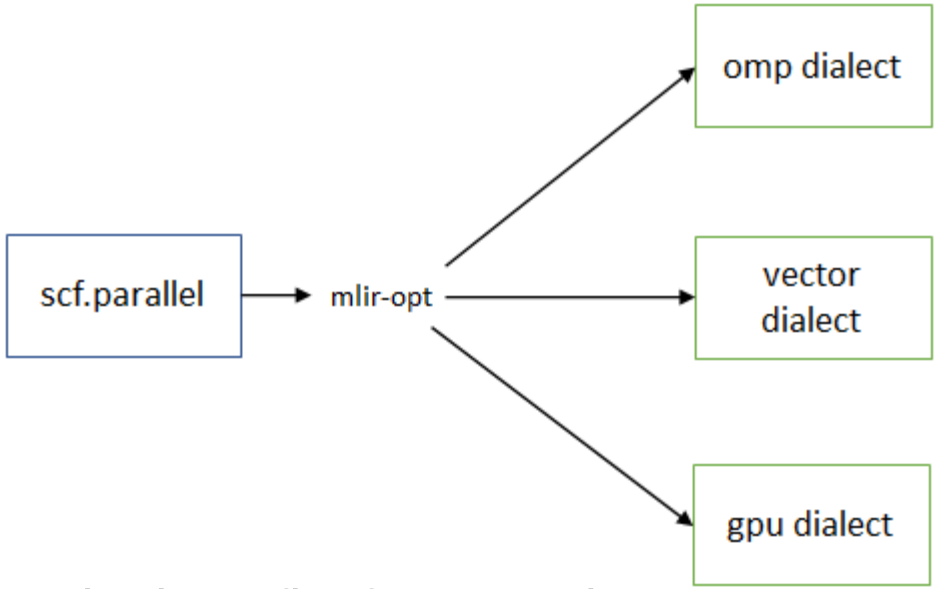
# Using scf.parallel

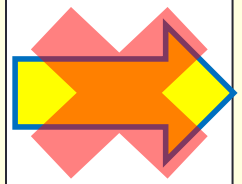
- We can leverage the *parallel* operation in the *scf* dialect
  - Which is an operation that represents a parallel loop




  - This really illustrates the benefit of MLIR, where we can use a high level construct such as this and then rely on existing transformations to lower it to a variety of targets

# But this needs some thought…..

```
%7 = "scf.for"(%4, %5, %6, %0) ({
^0(%8 : index, %9 : f32):
  %10 = "arith.addf"(%9, %1) : (f32, f32) -> f32
  "scf.yield"(%10) : (f32) -> ()
}) : (index, index, index, f32) -> f32
```



```
%7 = "scf.parallel"(%4, %5, %6, %0) ({
^0(%8 : index, %9 : f32):
  %10 = "arith.addf"(%9, %1) : (f32, f32) -> f32
  "scf.yield"(%10) : (f32) -> ()
}) : (index, index, index, f32) -> f32
```

- Unfortunately it isn't as simple as swapping the *for* operation with *parallel*
  - Because we are updating the result of the *addf* operation each iteration (%10 which is yielded and becomes %9 in the next operation)
  - This adds a loop carried dependency that must be considered when parallelising the loop, as otherwise the result will be incorrect
  - The solution is to wrap the *arith.addf* operation in the *reduce* operation of the *scf* dialect
    - Which informs MLIR of this relationship

# The transformation

```
%7 = "scf.parallel"(%4, %5, %6, %0) ({
^0(%8 : index):
  "scf.reduce"(%1) ({
    ^1(%lhs : f32, %rhs : f32):
      %11 = "arith.addf"(%lhs, %rhs) : (f32, f32) -> f32
      "scf.reduce.return"(%11) : (f32) -> ()
    }) : (f32) -> ()
  "scf.yield"() : () -> ()
}) {"operand_segment_sizes" = array<i32: 1, 1, 1, 1>} :
        (index, index, index, f32) -> f32
```

*scf.parallel* enables loops to be fused, where an arbitrary number of for and to bounds can be specified, along with their individual steps

*Known as varadic operands and we need to specify the number of these so MLIR can interpret them (here have one loop with one input SSA value)*

- Most of this pass is already provided, with you needing to fill in some missing parts as per the exercise sheet
  - See the sample solutions and ask us if this is unclear at all
- You can see how we are wrapping the *arith.addf* in the *scf.reduce* operation now, and also *scf.reduce.return* to return the result to the next iteration

# Lowering with MLIR

mlir-opt --pass-pipeline="builtin.module(loop-invariant-code-motion, **convert-scf-to-openmp**, convert-scf-to-cf, convert-cf-to-llvm{index-bitwidth=64}, convert-arith-to-llvm{index-bitwidth=64}, **convert-openmp-to-llvm**, convert-func-to-llvm, reconcile-unrealized-casts)" ex_two.mlir

- Lowering transformation passes are in blue
  - Lowering scf to the *omp* dialect to add in threaded parallelism
  - Then lowering the *omp* dialect to the *llvm* dialect
- Optimisation passes in red (this moves statements outside of the loop body where possible)
- Instructions to MLIR in green (here to instruct MLIR to put in explicit operations for undertaking implicit data conversion)

*scf-parallel-loop-specialization* will lower to the vector dialect, can also lower to the *gpu* dialect (see the exercise sheet for how to do this)