Lecture one

Introduction to MLIR and LLVM

HPC motivation

- In HPC we rely heavily on libraries and compilers, and a number of these have already been ported on-top of MLIR, with more to follow
- But we need to be realistic here, MLIR was only created in 2022, so whilst it is growing very rapidly, it is still developing and being enhanced
    - This is one of the exciting aspects, as we in the HPC community have the opportunity to engage and influence its development
    - The ecosystem has matured significantly in the last 18 months, so it is now a realistic opportunity to build on-top of this and to expect benefits

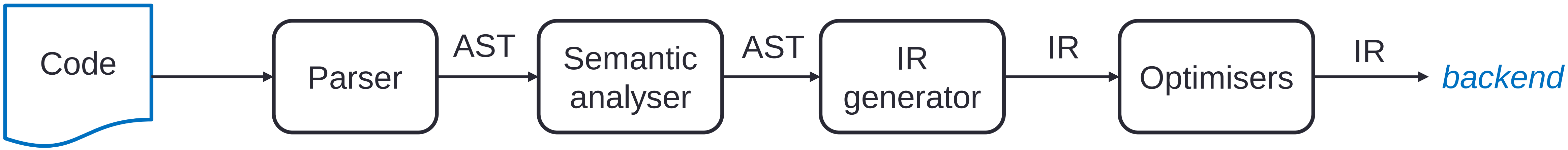
Technology overview

- MLIR is a framework for developing your own compiler Intermediate Representation (IR)
- Allowing different levels of abstraction to co-exist
  - Progressive lowering through these levels during compilation from one dialect to another
  - You the compiler/tool developer choose where these abstraction layers start & stop

- LLVM is a collection of modular compiler technologies that aids reuse
  - Contains the clang, flang etc compilers
- For our uses, the most interesting part are the backends which target different architectures
- We can interact with these by generating LLVM-IR

The challenge MLIR is looking to solve

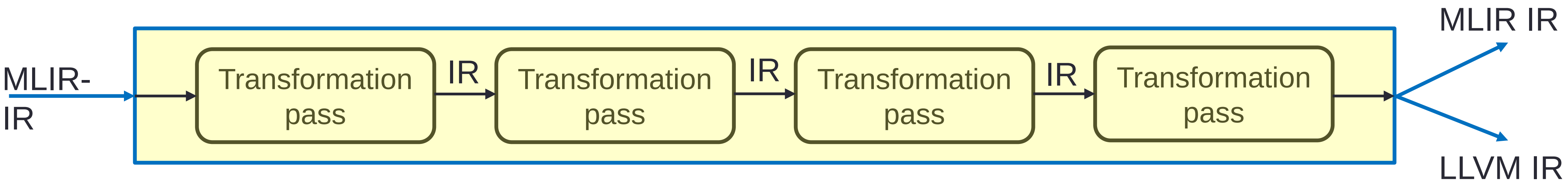
- Whilst LLVM has become very popular, much of the reuse is in the backend where LLVM-IR can target different architectures



- However, activities in the frontend can be extremely time consuming
  - Especially designing the IR, generating it and then and the optimisers
- This is where MLIR fits, providing a framework for defining and manipulating IRs
  - As well as many existing IRs and transformations to promote reuse

Executing MLIR

- LLVM provides the *mlir-opt* tool which accepts inputs and generates outputs
  - Can input MLIR format IR, output can be MLIR IR, LLVM IR etc
  - Can instruct the tool to undertake passes on the IR



- Other tools wrap this, such as Flang which is LLVM's Fortran compiler
  - Parses the Fortran code into it's own MLIR dialect (FIR) with other optional dialects, then undertakes transformation on the code before generating the object files

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MLIR-IR is human readable

- Currently MLIR-IR can be viewed at each stage and is (fairly!) easy to read
- Can be useful for debugging

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

- In this example we are already seeing some of MLIR's standard dialects being mixed and matched
  - The *function* dialect which marks this as a function, the call, and the return
  - The *arith* dialect that undertakes the integer addition (*addi)*
  - The *cf* dialect that undertakes the branch (*br)*
- Could add our own dialects and include them here too

MLIR-IR is the ecosystem

- MLIR provides the overarching framework here but known nothing about specific instructions

```
func @testFunction(%arg0: i32) -> i32 {
 %x = "any_unknown_operation_here"(%arg0, %arg0) : (i32, i32) -> i32
 %y = "my_increment"(%x) : (i32) -> i32
 return %y : i32
}
```

- These will be caried through the transformation passes and it is expected that some of the transformations know how to handle these
- Therefore MLIR is an open, highly pluggable ecosystem where new dialects and new transformations can be created without having to modify others

- But there are standard dialects provided which include standard types

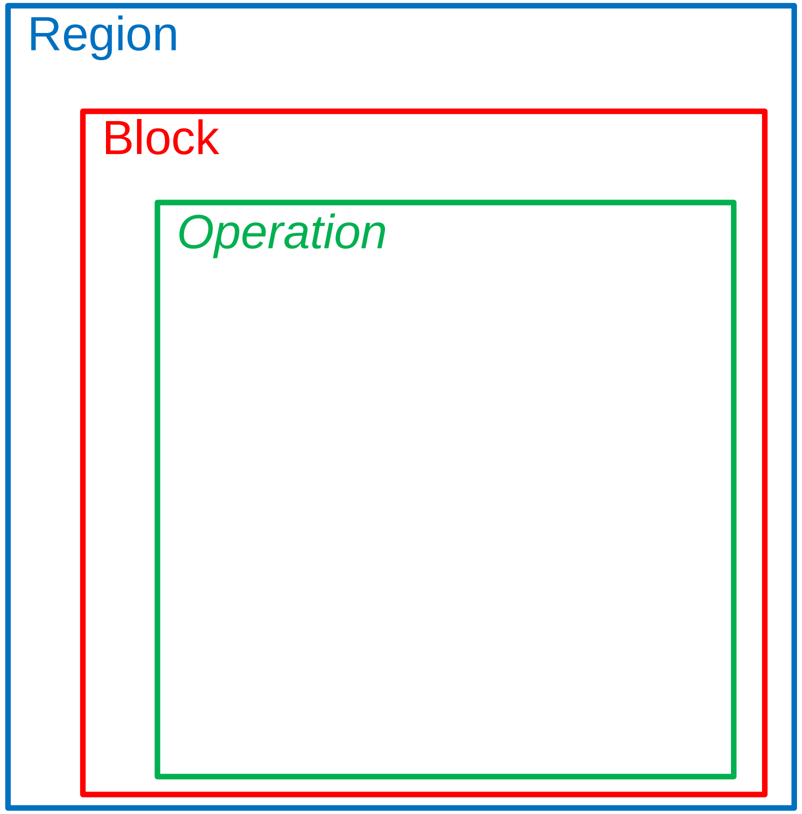
How do we get this to LLVM-IR?

- The standard dialects include transformations to generate LLVM-IR

- For your own dialects you will need to either write your own transformations to generate LLVM-IR or alternatively transform into a dialect (e.g. a standard one) for this
  - There is nothing special about LLVM-IR from this perspective, you could also write transformations to convert your IR into target languages such as C, Fortran, Python etc and emit that

MLIR key concepts…

- MLIR is based on a graph style data structure of nodes which are called *Operations* and edges called *values*.
- Regions contain an ordered set of blocks, and blocks contain an ordered set of operations
  - Operations can also contain regions, and hence hierarchical structures can be expressed
- Operations are where most of the definition occurs
  - Can represent pretty much anything; functions definitions, function calls, variable allocation, conditionals, assignment etc
  - Operations can be arbitrarily extended



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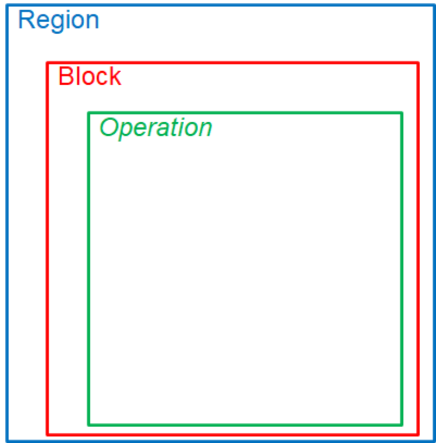
Operations and their children

- Operations can be associated with regions, other operations, and attributes
- Attributes provide the ability to associate constant data with some operation
  - Expressed as a dictionary, mapping attribute names (the key) to their values
  - MLIR's *builtin* dialect defines an extensive set of attribute value types, including arrays, dictionaries, strings, and integers.

  - [TODO] – output of MLIR conditional – then have arrows illustrating operation children (attributes, other operations, region etc).

Blocks

- Blocks contain a list of operations and can be thought of as executing these in order
- Blocks accept an optional list of arguments similar to a function

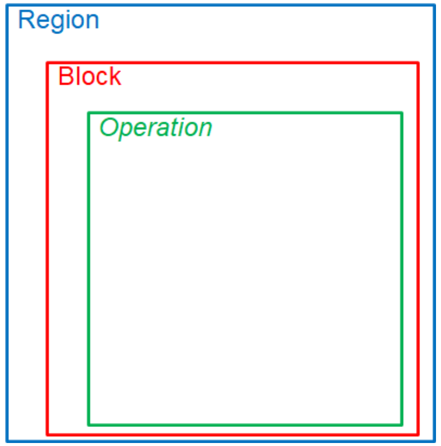



```
func.func @simple(i64, i1) -> i64 {
^bb0(%a: i64, %cond: i1): // Code dominated by ^bb0 may refer to %a
  cf.cond_br %cond, ^bb1, ^bb2

^bb1:
  cf.br ^bb3(%a: i64)    // Branch passes %a as the argument

^bb2:
  %b = arith.addi %a, %a : i64
  cf.br ^bb3(%b: i64)    // Branch passes %b as the argument

// ^bb3 receives an argument, named %c, from predecessors
// and passes it on to bb4 along with %a. %a is referenced
// directly from its defining operation and is not passed through
// an argument of ^bb3.
^bb3(%c: i64):
  cf.br ^bb4(%c, %a : i64, i64)

^bb4(%d : i64, %e : i64):
  %0 = arith.addi %d, %e : i64
  return %0 : i64   // Return is also a terminator.
}
```

- Here we have a function containing five blocks, where blocks bb0, bb3, and bb4 accept arguments
- Can see the use of the *cf* dialect to branch between these blocks
- The last block is the terminating block

Code example reproduced from https://mlir.llvm.org/docs/LangRef/

Regions



- A region contains an ordered list of blocks
- Regions must be contained within operations, therefore they are hierarchical
  - The body of a function is an example of a region, contained within the function definition operation
- Regions also provide encapsulation, where one can only branch to blocks within the same region

Types

- MLIR provides its own type system
  - Again, MLIR provides the framework and the dialects provide the actual types themselves
  - Any number of types can be defined by dialects
  - Types can accept any number of parameters

- Can also provide aliases
  - i.e. i32 is an alias for the IntegerType of width 32
  - f64 is an alias for the FloatType of width 64
  - Some types accept parameters – such as width, kind (useful for Fortran)

Defining dialects

- Dialects are the mechanism by which the MLIR ecosystem is extended
- Can define new operations, new attributes, and new types
  - Each attribute has a unique name and this is prefixed to each of these
- Dialects are consumed by passes, with conversions between dialects common

- Dialects provided as part of MLIR are:
  - acc
  - affine
  - amdgpu
  - amx
  - arith
  - arm_neon
  - arm_sve
  - async
  - bufferization
  - cf
  - complex
  - dlti
  - emitc
  - func
  - gpu
  - index
  - linalg
  - LLVM
  - math
  - memref
  - ml_program
  - nvgpu
  - nvvm
  - omp
  - pdl
  - pdl_interp
  - quant
  - rocdl
  - scf
  - shape
  - sparse_tensor
  - tensor
  - vector
  - x86vector
  - Builtin
  - SPIR-V
  - TOSA
  - Transform

Example flow……

- We will see this in more detail in the hands-on activities, but to give you a feeling for it now

```
user@login01:~$ mlir-opt --convert-func-to-llvm ir.mlir | mlir-translate -mlir-to-llvmir | clang -x ir -o test -
```

Provide some MLIR file as input to the *mlir-opt* call which provides numerous transformations

Once in its final form the *mlir-translate* tool will convert from MLIR to a number of output formats, here we are generating LLVM IR

The standard LLVM IR is then provided to Clang which will compile it to an object file or executable

- But where do we get the MLIR input file (here *ir.mlir*) in the first place?
  - That's the job of our language specific frontend and we will see this in more detail in the hands on activities

Conclusions

- MLIR is a very powerful framework, promoting reuse of infrastructure especially because it is backed by LLVM
  - You often see it presented as *doing properly* what from experience with LLVM they wish they had changed with that framework!
  - This is probably a little unfair to LLVM, but certainly it is based on all the lessons learnt
- We have focussed on the overarching concepts in this lecture
  - Regions, which contain blocks, which contain operations – which themselves can contain regions.
  - The ability to define dialects and transformations, and for these to coexist together
  - The fact that numerous standard dialects and transformations are provided *out-of-the-box*