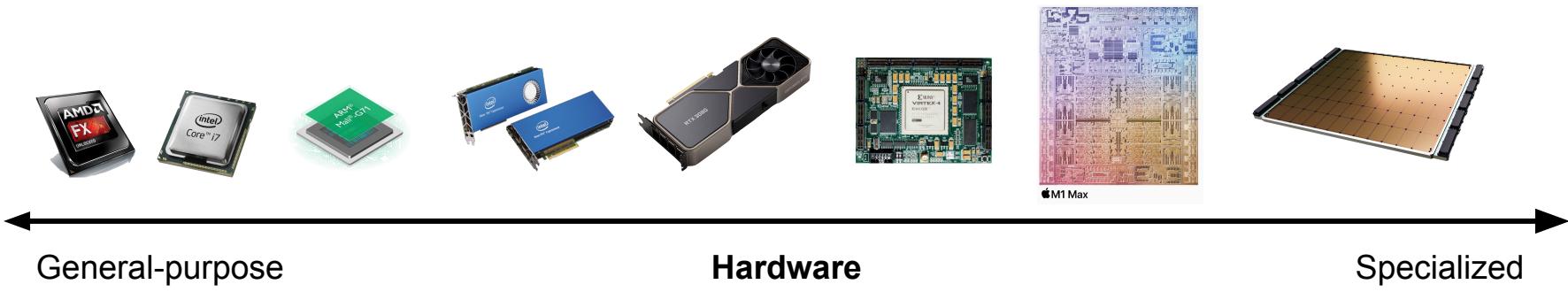


# Python-native domain-specific compilation for low-level systems with **xDSL**

Tobias Grosser

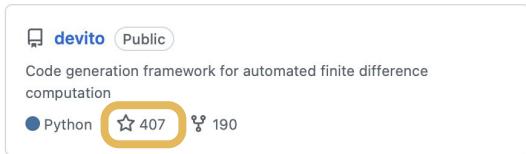


How to compile  
specialized software to specialized hardware?



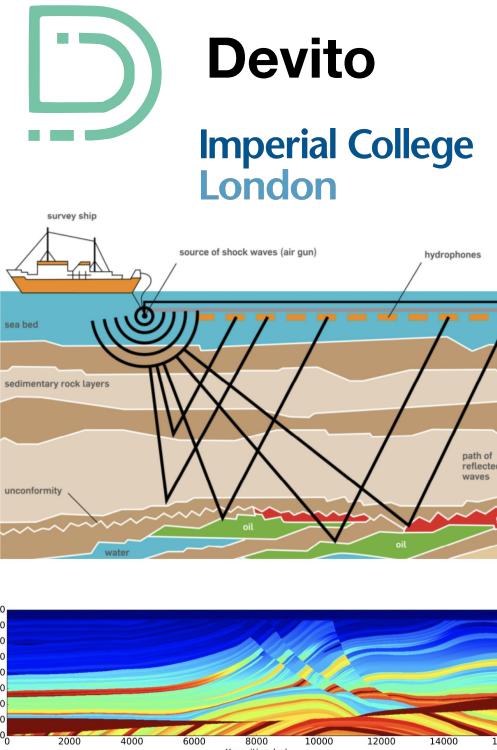
# How do we currently build specialized Compilers?

## Example 1: Devito HPC DSL



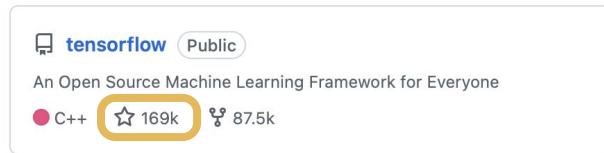
- < 50,000 lines of code
- Compiler implemented in Python
- Uses three IRs to compile
- Applies many classical loop optimizations
- Support for GPUs, no support for hardware accelerators

**Usability** and **performance**, portable on CPUs, GPUs,  
but **limited hardware support** and **optimizations**



# How do we currently build specialized Compilers?

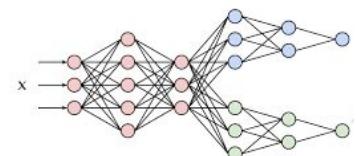
## Example 2: TensorFlow, Google's ML Framework



- > 2,500,000 lines of code
- Compiler implemented in Python & C++
- Uses two IRs with > 500 different types of expressions
- Applies many classical loop optimizations
- Great Performance & Support for custom hardware: TPU



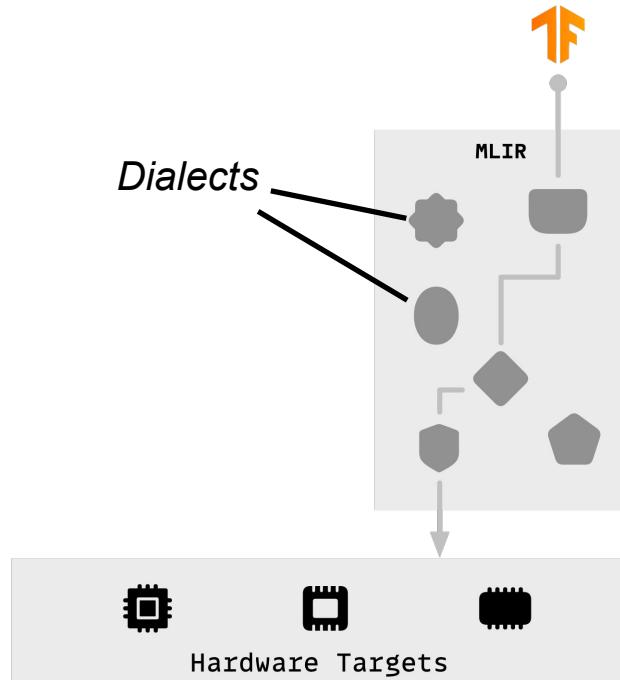
# TensorFlow



**Huge effort** to build and maintain, but **great performance!**

# MLIR — Multi-Level Intermediate Representation

An LLVM subproject for building reusable and extensible compiler infrastructure



# Simple example in MLIR

- A DSL that is aware of stacks

```
fn demo(stack: &stack<i32>) -> i32 {  
    i32 c = 5;  
    stack.push(c);  
    return stack.pop();  
}
```

Your Tool



**MLIR FORMAT**  
**(sequence of operations with child regions)**  
+ a selection of dialects

# Simple example in MLIR

- A DSL that is aware of stacks

```
fn demo(stack: &stack<i32>) -> i32 {  
    i32 c = 5;  
    stack.push(c);  
    return stack.pop();  
}
```

```
func.func @demo(%stack: ???) -> i32 {  
  
    func.return %res  
}
```

Your Tool



# Simple example in MLIR

- A DSL that is aware of stacks

```
fn demo(stack: &stack<i32>) -> i32 {  
    i32 c = 5;  
    stack.push(c);  
    return stack.pop();  
}
```

```
func.func @demo(%stack: ???) -> i32 {  
    %c = arith.constant 5 : i32  
  
    func.return %res  
}
```

Your Tool



# Simple example in MLIR

- A DSL that is aware of stacks

## Stack Dialect

```
stack.stack<T>
```

```
stack.push %stack <- %val : T  
stack.pop  %stack           : T
```

# Simple example in MLIR

- A DSL that is aware of stacks

```
fn demo(stack: &stack<i32>) -> i32 {  
    i32 c = 5;  
    stack.push(c);  
    return stack.pop();  
}
```

Your Tool

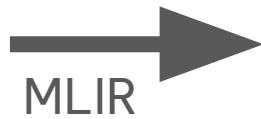


```
func.func @demo(%stack: stack.stack<i32>) -> i32 {  
    %c = arith.constant 5 : i32  
    stack.push %stack <- %c : i32  
    %res = stack.pop %stack : i32  
    func.return %res  
}
```

# Simple example in MLIR

- A DSL that is aware of stacks

```
func.func @demo(%stack: stack.stack<i32>) -> i32 {  
    %c = arith.constant 5 : i32  
    stack.push %stack <- %c : i32  
    %res = stack.pop %stack : i32  
    func.return %res  
}
```



```
func.func @demo(%stack: stack.stack<i32>) -> i32 {  
    %c = arith.constant 5 : i32  
    func.return %c  
}
```

*(with your domain-specific rewrite)*

# Simple example in MLIR

- A DSL that is aware of stacks

```
func.func @demo(%stack: stack.stack<i32>) -> i32 {  
    %c = arith.constant 5 : i32  
    func.return %c  
}
```



```
llvm.func @demo(%stack: llvm.ptr) -> i32 {  
    %c = llvm.constant 5 : i32  
    llvm.return %c  
}
```



MLIR is really nice!



MLIR is really nice!

...but it's very complicated



@



UNIVERSITY OF  
CAMBRIDGE



**Research**



**Open-Source Development**



**Teaching**  
(150 students / year)



Professor

John

Smith





SSA and Operations

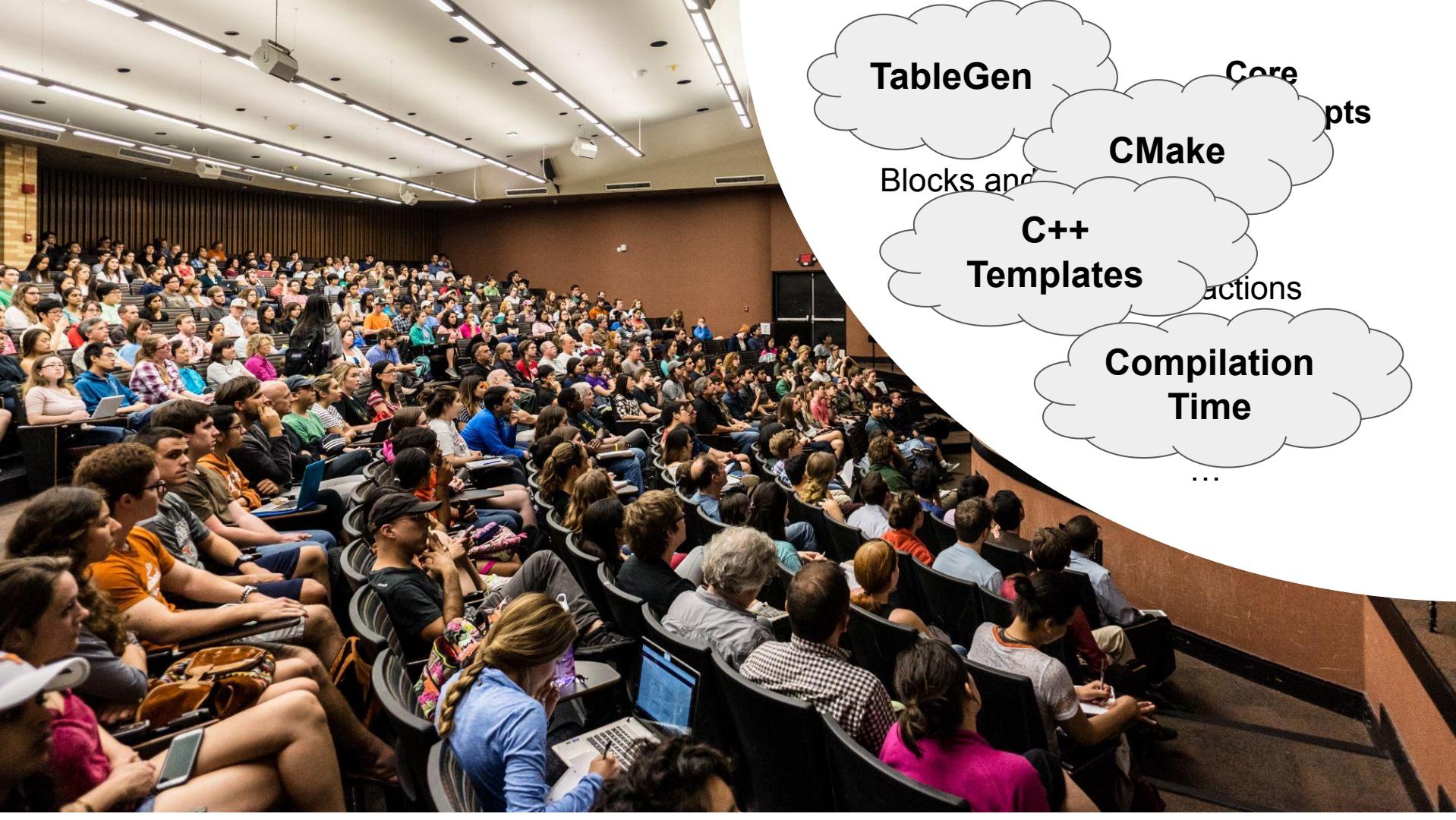
Core  
Concepts

Blocks and Regions

Dialects as abstractions

Peephole rewrites

...



TableGen

Core  
pts

CMake

Blocks and

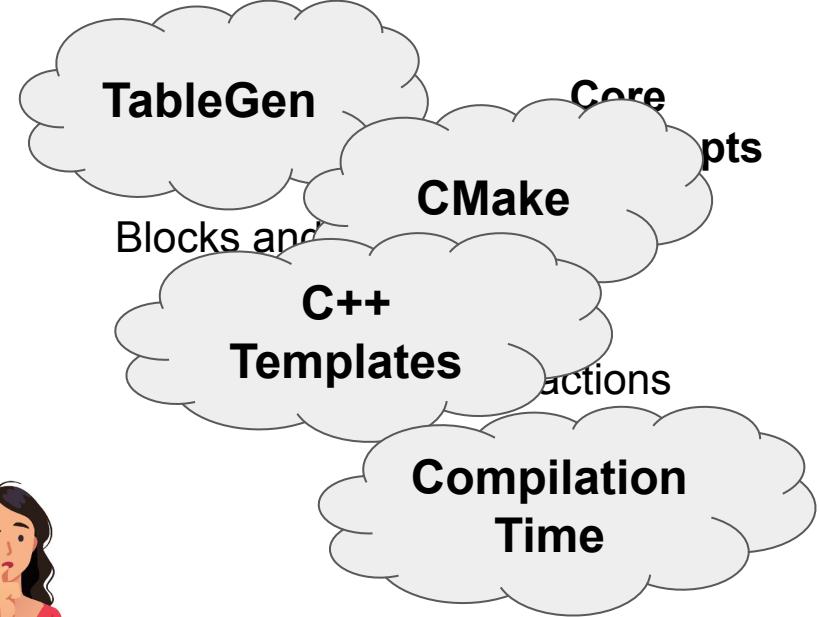
C++  
Templates

Actions

Compilation  
Time

...

# How to teach MLIR?



*MLIR is hard to get started with!*

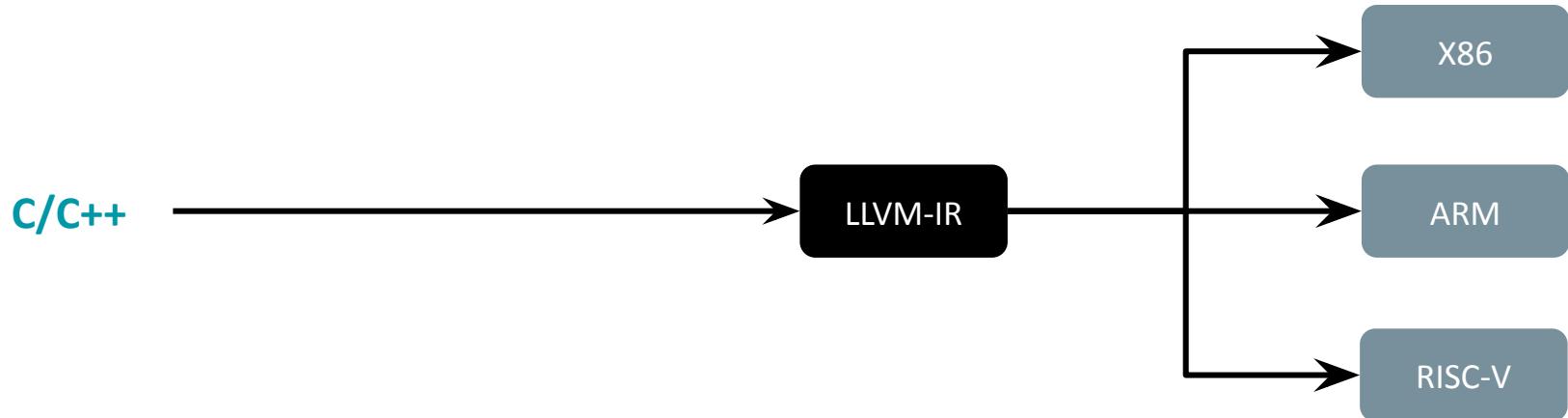
# Bringing in the MLIR ecosystem

xDSL is a Python implementation of the MLIR concepts

- Focus on *approachability*
- *Reuse* of existing concepts implemented in a simpler way
- *Expands* on MLIR concepts
- Making compiler frameworks *interoperable*

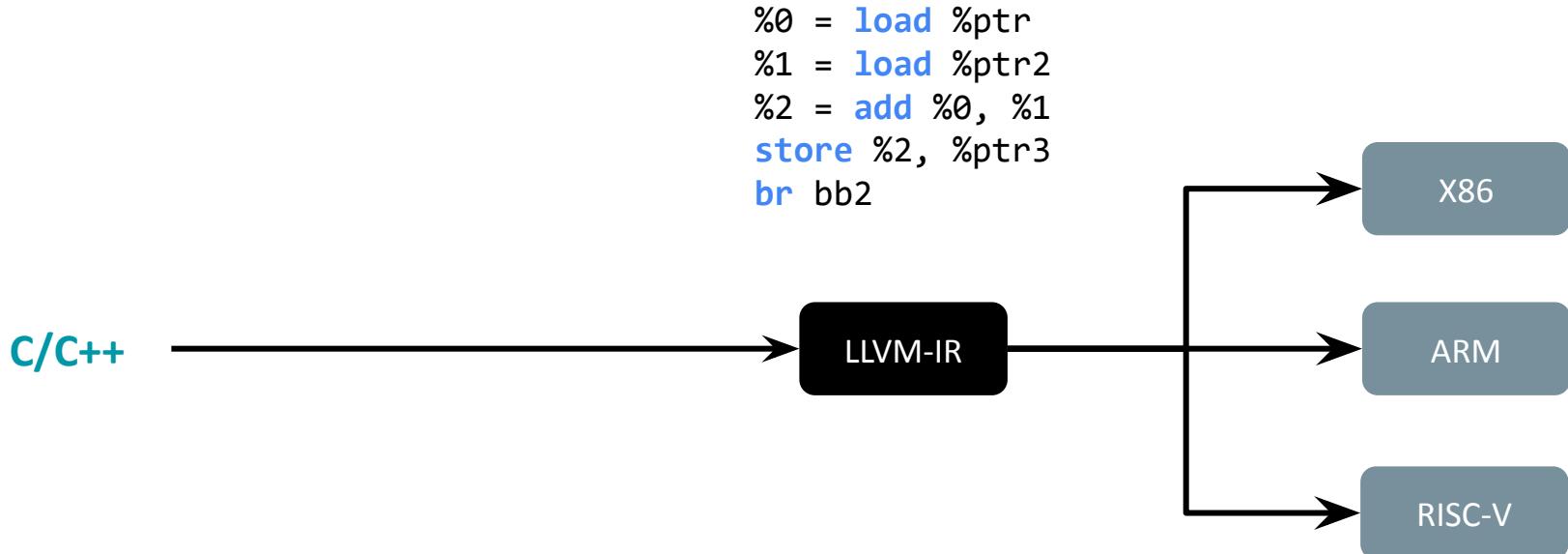


# Compiler Pipelines

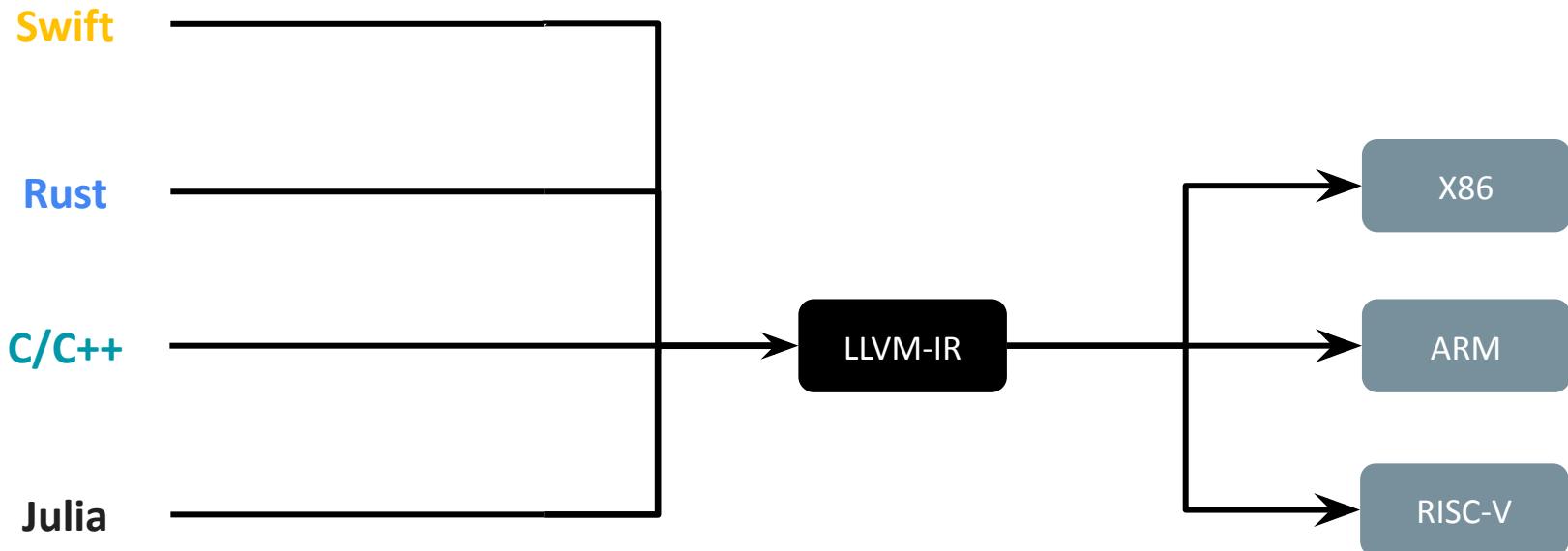


# Compiler Pipelines

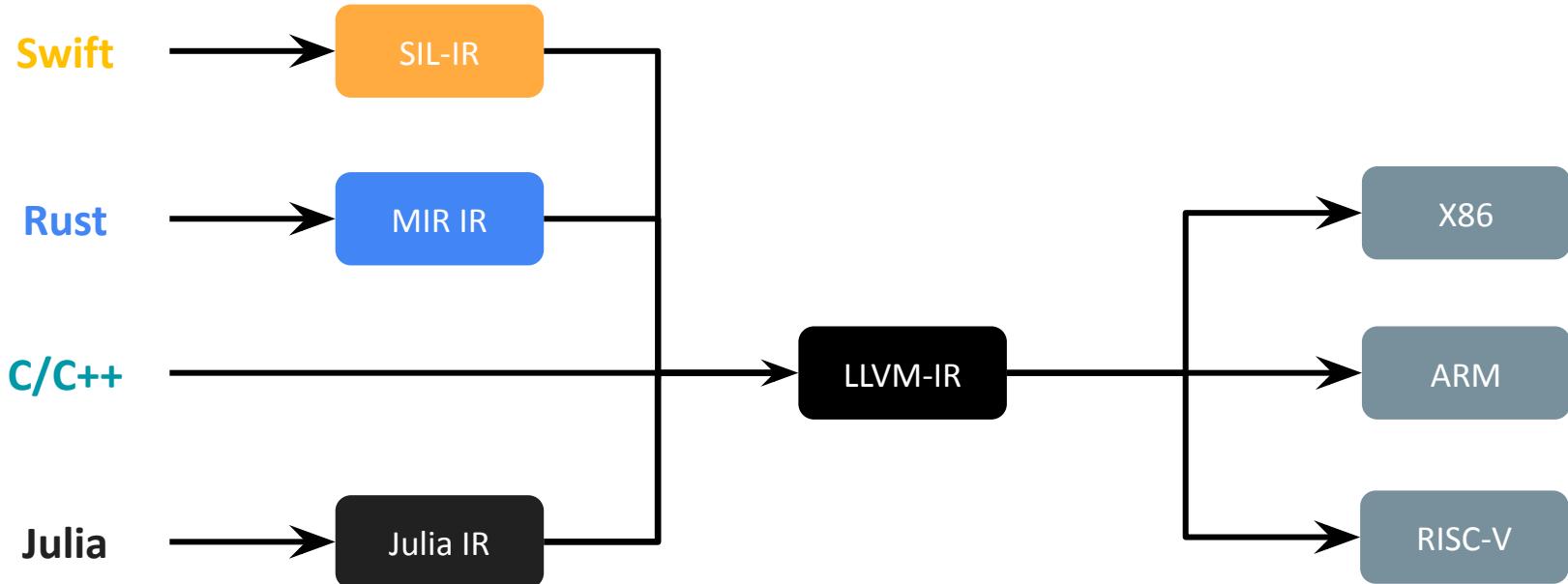
Intermediate Representations (IRs) are the central abstractions in a compiler.



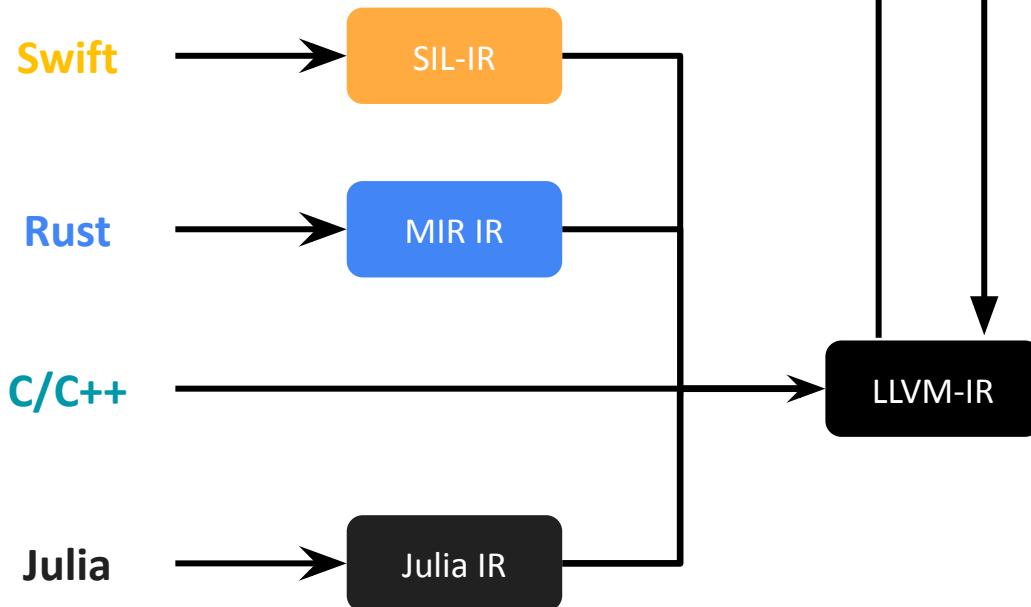
# Compiler Pipelines



# Compiler Pipelines



# Compiler Pipelines

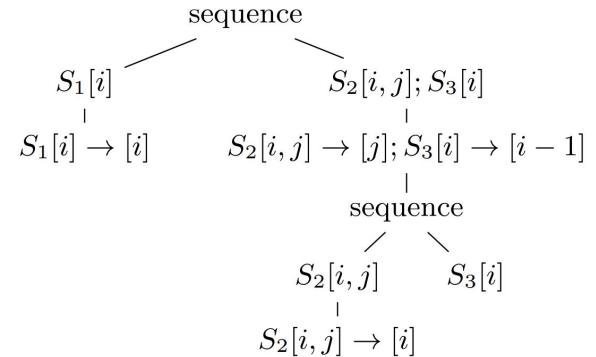


Polly

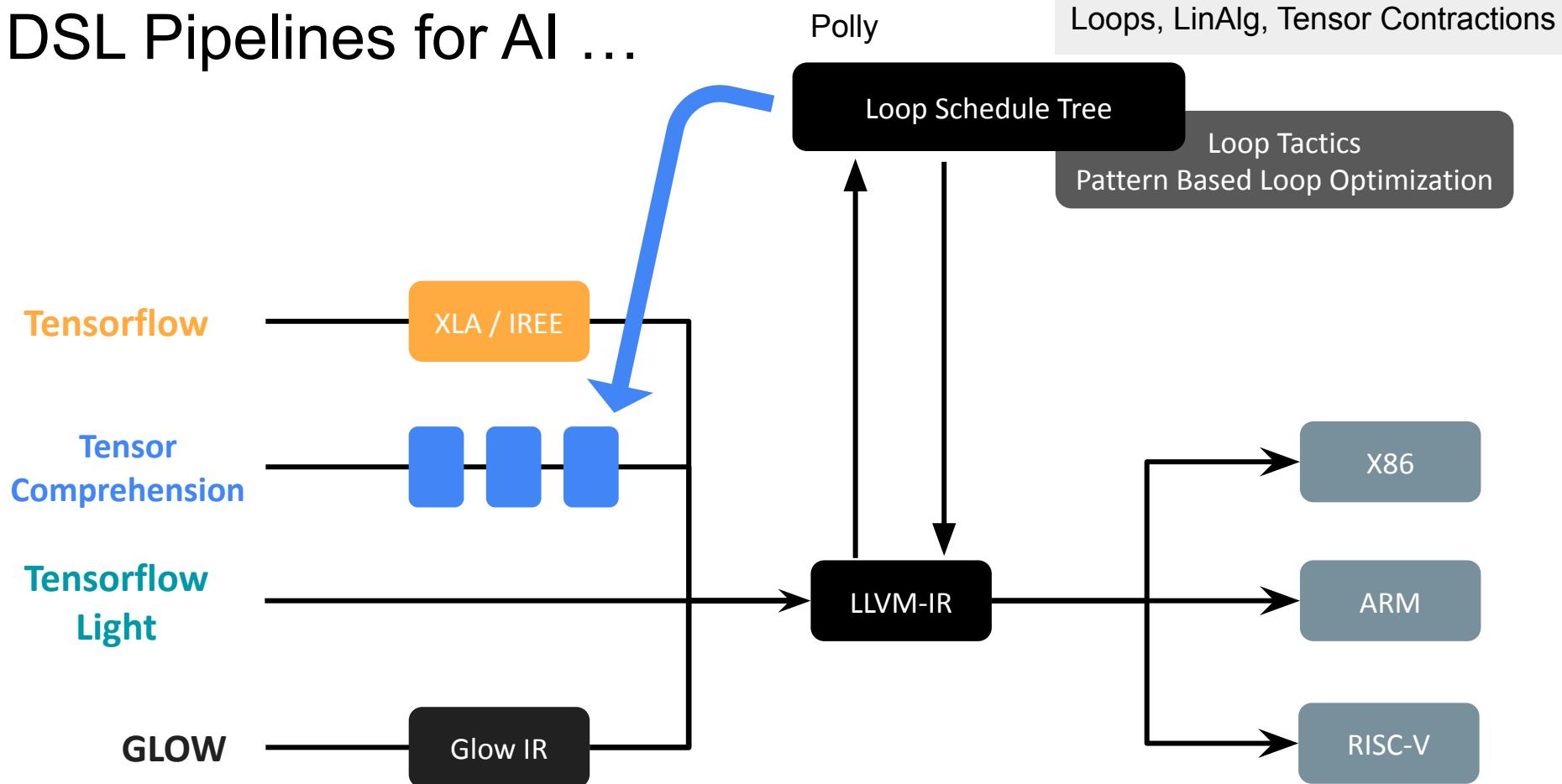
Loops, LinAlg, Tensor Contractions

Loop Schedule Tree

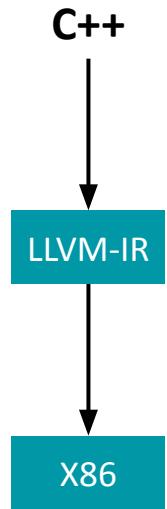
Loop Tactics  
Pattern Based Loop Optimization



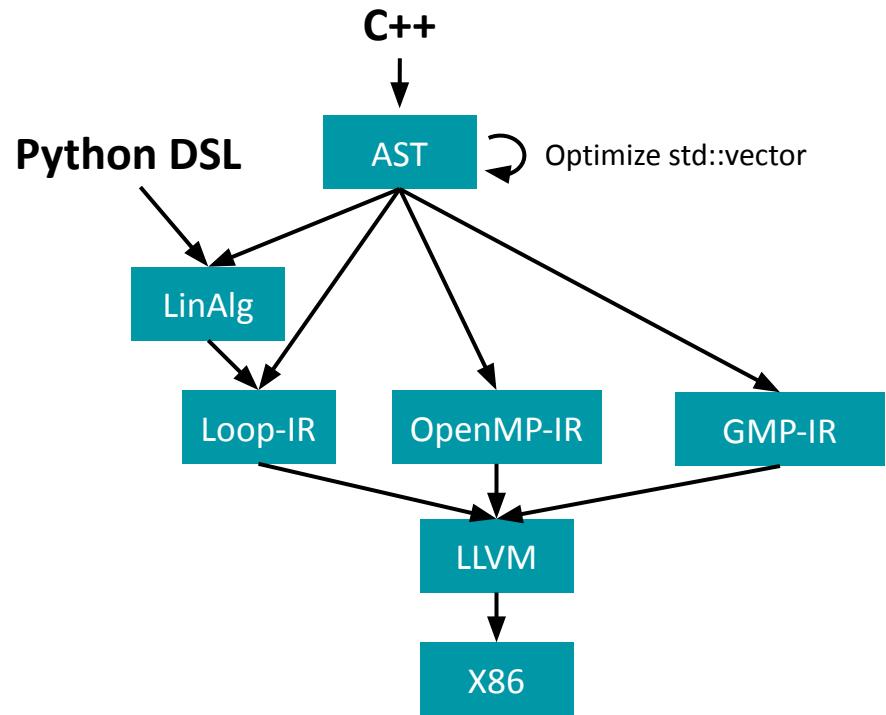
# DSL Pipelines for AI ...



## *Traditional Compilation*



## *New: Multi-Level Rewriting*



# MLIR — Multi-Level Intermediate Representation

## Example: Matrix Multiplication in MLIR

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

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

**Operations**  
represent computations

**Regions & Blocks**  
allow sequencing and nesting of operations

**Attributes**  
represent additional static information

**Types**  
ensure consistency of the overall program

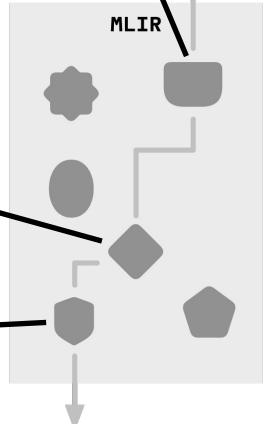
# MLIR — Multi-Level Intermediate Representation

## Progressive Lowering from Application Domain to Hardware

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

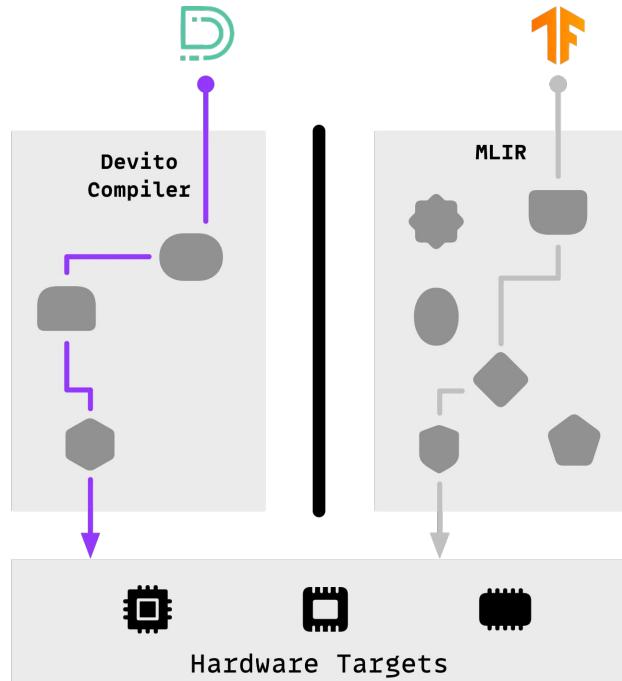
```
affine.for %i = 0 to %n {\n    ...\n    %sum  = addf %a, %b : f32\n    ...\n}
```

```
gpu.launch(%gx,%gy,%c1,%lx,%c1,%c1) {\n    ^bb0(%bx: index, %by: index, %bz: index,\n        %tx: index, %ty: index, %tz: index,\n        %num_bx: index, %num_by: index, %num_bz: index,\n        %num_tx: index, %num_ty: index, %num_tz: index)\n    ...\n    %sum  = addf %a, %b : f32\n    ...\n}
```



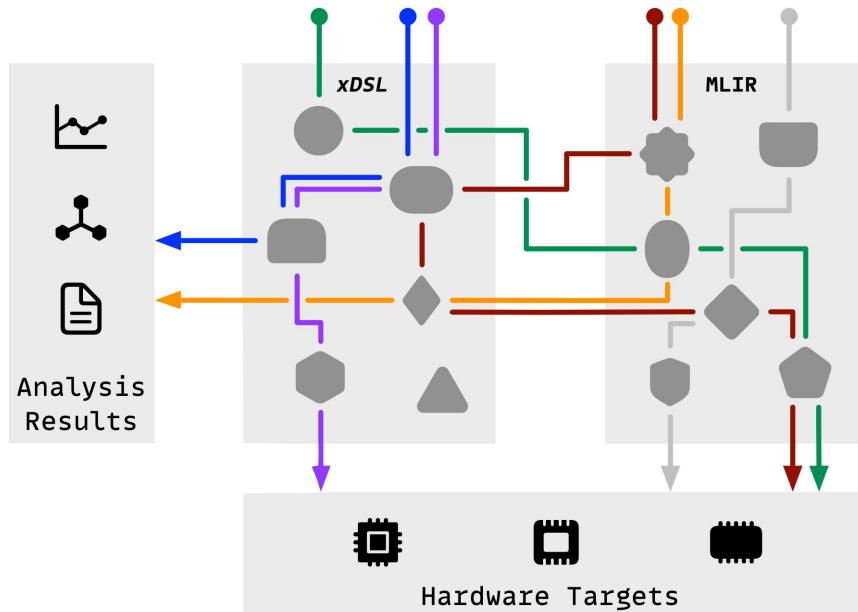
# *Problem: Isolated Compiler Ecosystems*

Each DSL reimplements the same IRs and optimizations



# xDSL: a *Sidekick* to MLIR

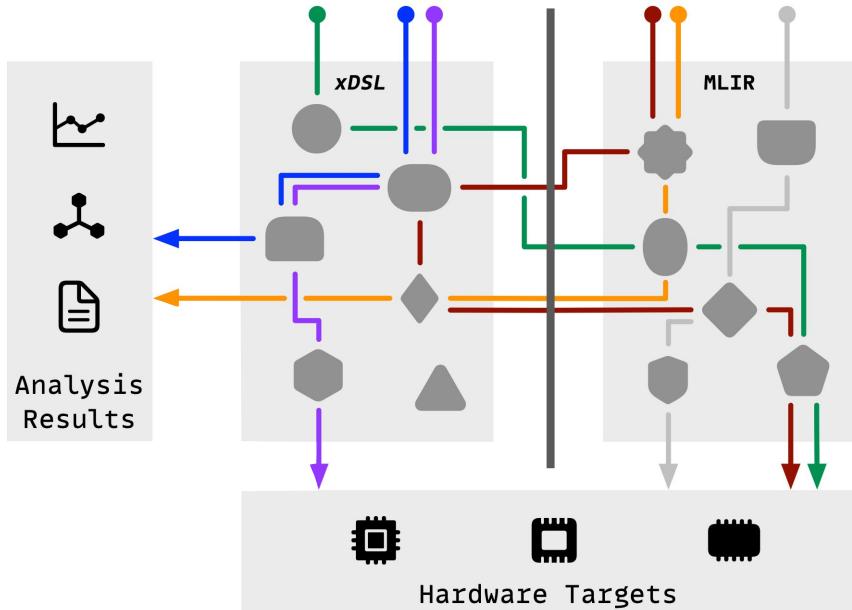
Making the MLIR ecosystem accessible and extensible from Python



- Python-native end-to-end compilers
- Prototyping new compiler design ideas
- Analysing the compilation flow
- Pairing high-level Python DSLs with existing low-level MLIR dialects and optimizations

# xDSL: a *Sidekick* to MLIR

How does it work?



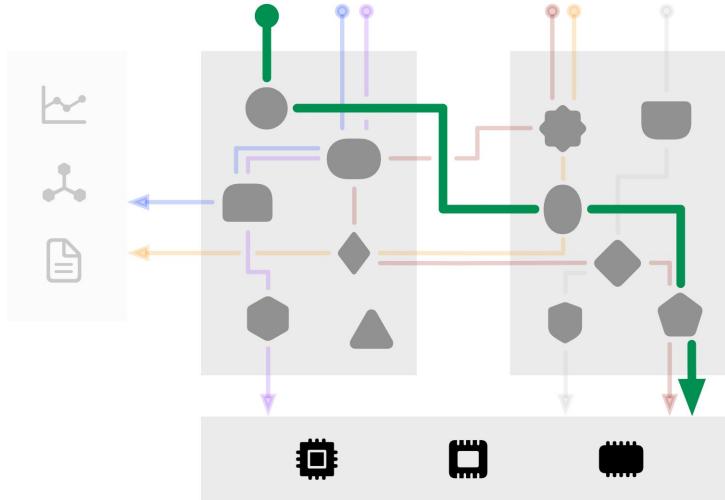
Translation consists of:

- Programs ✓
- IR Definitions ✓
- Transformations ?

# Use Case

## Building a high-level Python DSL with existing low-level MLIR dialects

- *User:*
  - Domain experts, e.g., computational scientists or database experts
- *Needs:*
  - Productivity is (often) more important than compilation speed
- *Existing Workflows:*
  - Build isolated compiler ecosystem (such as Devito)
- *The xDSL Approach:*
  - Embed high-level DSL in Python for ease of use
  - Use xDSL dialects in Python and then lower to common dialects that are optimized in MLIR

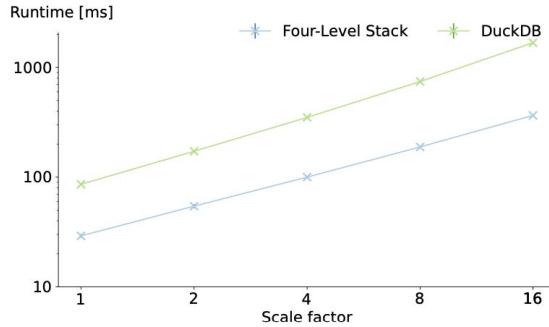


# Use Case

## Building a high-level Python DSL with existing low-level MLIR dialects

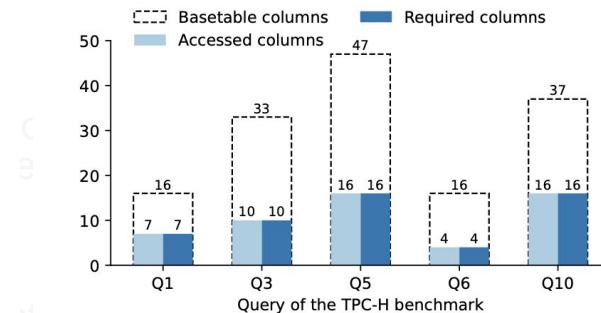
- *User:*

- Domain experts computational scientists or database engineers



- We implemented a database DSL using xDSL outperforming the in-memory database DuckDB

- Build high-level DSL interface in Python
- Use xDSL dialects in Python and then lower to common dialects that are optimized in MLIR



Reduction of basetable column accesses implemented as a compiler optimization pass in Python with xDSL

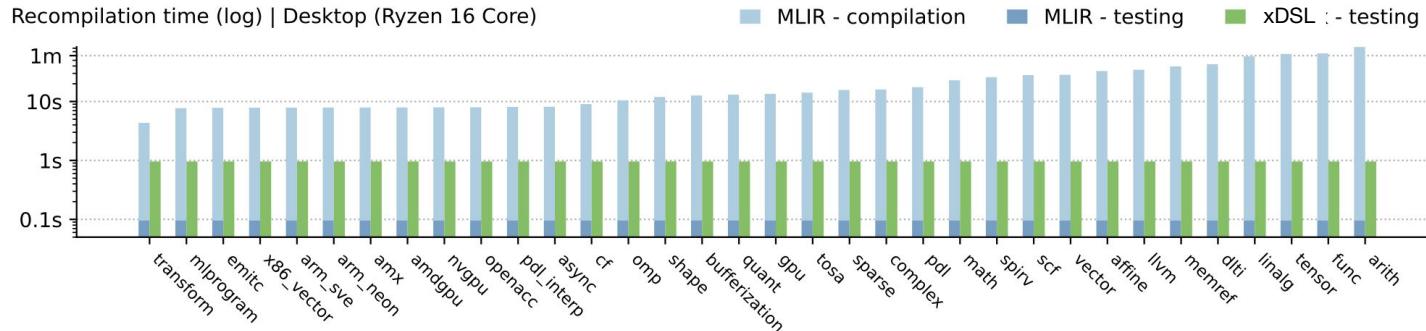
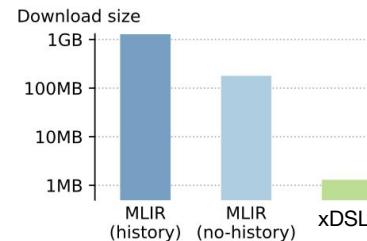
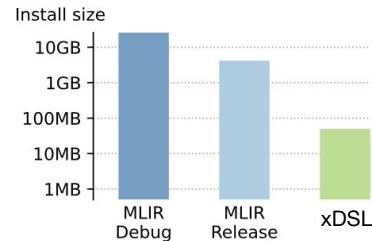
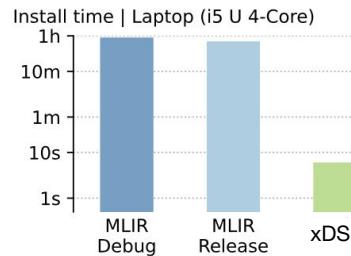
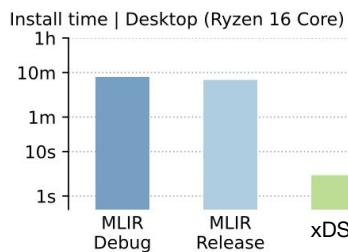


We currently work with colleagues from Imperial to integrate Devito & MLIR with xDSL

# xDSL boosts Developers Productivity

Much shorter install times

| Much faster recompilation times





# An MPI Abstraction for MLIR

Anton Lydike, Nick Brown, Jeff Hammond

# Scope and Goals

```
char message[20];
int myrank;
```

```
myrank = 0

message = "Hello, there"

MPI_Send message to rank 1
```

```
myrank = 1

MPI_Recv into message from rank 0

message = "Hello, there"
```

# Scope and Goals

```
char message[20];
int myrank;

MPI_Init(NULL, NULL);

MPI_Comm_rank(MPI_COMM_WORLD, &myrank);

if (myrank == 0) /* code for process zero */
{
    strcpy(message, "Hello, there");
    MPI_Send(message, strlen(message) + 1, MPI_CHAR,
             1, 0, MPI_COMM_WORLD);
}
else if (myrank == 1) /* code for process one */
{
    MPI_Recv(message, 20, MPI_CHAR, 0, 0,
             MPI_COMM_WORLD, MPI_STATUS_IGNORE);
    printf("received :%s\n", message);
}

MPI_Finalize();
```

# Scope and Goals

```
char message[20];
int myrank;

MPI_Init(NULL, NULL); → mpi.init

MPI_Comm_rank(MPI_COMM_WORLD, &myrank); → %zero = arith.constant 0 : i32
                                            %one = arith.constant 1 : i32
                                            %message = memref.alloca() : memref<12xi8>
                                            %data = memref.get_global @hello_there : memref<12xi8>

if (myrank == 0) /* code for process zero */
{
    strcpy(message, "Hello, there");
    MPI_Send(message, strlen(message) + 1, MPI_CHAR,
             1, 0, MPI_COMM_WORLD); → %myrank = mpi.comm_rank : i32
                                %is_rank_zero = arith.cmpi eq, %myrank, %zero : i32
                                scf.if %is_rank_zero
                                { // code for process zero
                                    memref.copy %data, %message : memref<12xi8> to memref<12xi8>
                                    mpi.send(%message, %one, %zero) : (memref<12xi8>, i32, i32)
                                } else { // code for process one
                                    mpi.recv(%message, %zero, %zero) : (memref<12xi8>, i32, i32)
                                    printf.print_format "received: {}\n" %message : memref<12xi8>
                                }
}

MPI_Finalize(); → mpi.finalize
```

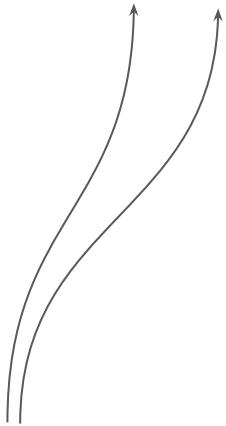
MPI\_Init  
MPI\_Comm\_rank  
MPI\_Send  
MPI\_Recv  
MPI\_Finalize

# Modelling MPI

MPI\_Init ✓  
MPI\_Comm\_rank  
MPI\_Send  
MPI\_Recv  
MPI\_Finalize

# Modelling MPI

```
MPI_Init(NULL, NULL);
```



```
mpi.init() : () -> ()
```

- Simplify default constant arguments

MPI\_Init ✓  
MPI\_Comm\_rank ✓  
MPI\_Send  
MPI\_Recv  
MPI\_Finalize

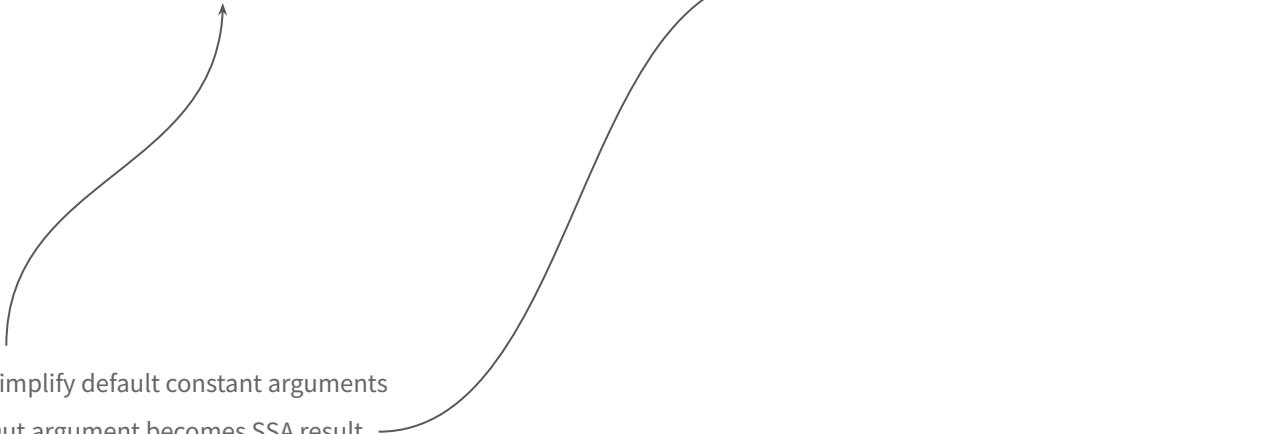
# Modelling MPI

```
MPI_Init(NULL, NULL);
```

```
MPI_Comm_rank(MPI_COMM_WORLD, &myrank);
```

```
mpi.init() : () -> ()
```

```
%myrank = mpi.comm_rank() : () -> i32
```



- Simplify default constant arguments
- Out argument becomes SSA result

# Modelling MPI

MPI\_Init ✓  
MPI\_Comm\_rank ✓  
MPI\_Send ✓  
MPI\_Recv  
MPI\_Finalize

```
MPI_Init(NULL, NULL);
```

```
mpi.init() : () -> ()
```

```
MPI_Comm_rank(MPI_COMM_WORLD, &myrank);
```

```
%myrank = mpi.comm_rank() : () -> i32
```

```
MPI_Send(message, strlen(message) + 1, MPI_CHAR,  
        1, 0, MPI_COMM_WORLD);
```

```
mpi.send(%message, %one, %zero)  
: (memref<12xi8>, i32, i32) -> ()
```

- Simplify default constant arguments
- Out argument becomes SSA result
- Pointer + Size + Datatype = memref

# Modelling MPI

MPI\_Init ✓  
MPI\_Comm\_rank ✓  
MPI\_Send ✓  
MPI\_Recv ✓  
MPI\_Finalize

```
MPI_Init(NULL, NULL);
```

```
mpi.init() : () -> ()
```

```
MPI_Comm_rank(MPI_COMM_WORLD, &myrank);
```

```
%myrank = mpi.comm_rank() : () -> i32
```

```
MPI_Send(message, strlen(message) + 1, MPI_CHAR,  
1, 0, MPI_COMM_WORLD);
```

```
mpi.send(%message, %one, %zero)  
: (memref<12xi8>, i32, i32) -> ()
```

```
MPI_Recv(message, 20, MPI_CHAR, 0, 0,  
MPI_COMM_WORLD, MPI_STATUS_IGNORE);
```

```
mpi.recv(%message, %zero, %zero)  
: (memref<12xi8>, i32, i32) -> ()
```

- Simplify default constant arguments
- Out argument becomes SSA result
- Pointer + Size + Datatype = memref

# Modelling MPI

```
MPI_Init(NULL, NULL);

MPI_Comm_rank(MPI_COMM_WORLD, &myrank);

MPI_Send(message, strlen(message) + 1, MPI_CHAR,
         1, 0, MPI_COMM_WORLD);

MPI_Recv(message, 20, MPI_CHAR, 0, 0,
         MPI_COMM_WORLD, MPI_STATUS_IGNORE);

MPI_Finalize();
```

MPI_Init	✓
MPI_Comm_rank	✓
MPI_Send	✓
MPI_Recv	✓
MPI_Finalize	✓

```
mpi.init() : () -> ()

%myrank = mpi.comm_rank() : () -> i32

mpi.send(%message, %one, %zero)
: (memref<12xi8>, i32, i32) -> ()

mpi.recv(%message, %zero, %zero)
: (memref<12xi8>, i32, i32) -> ()

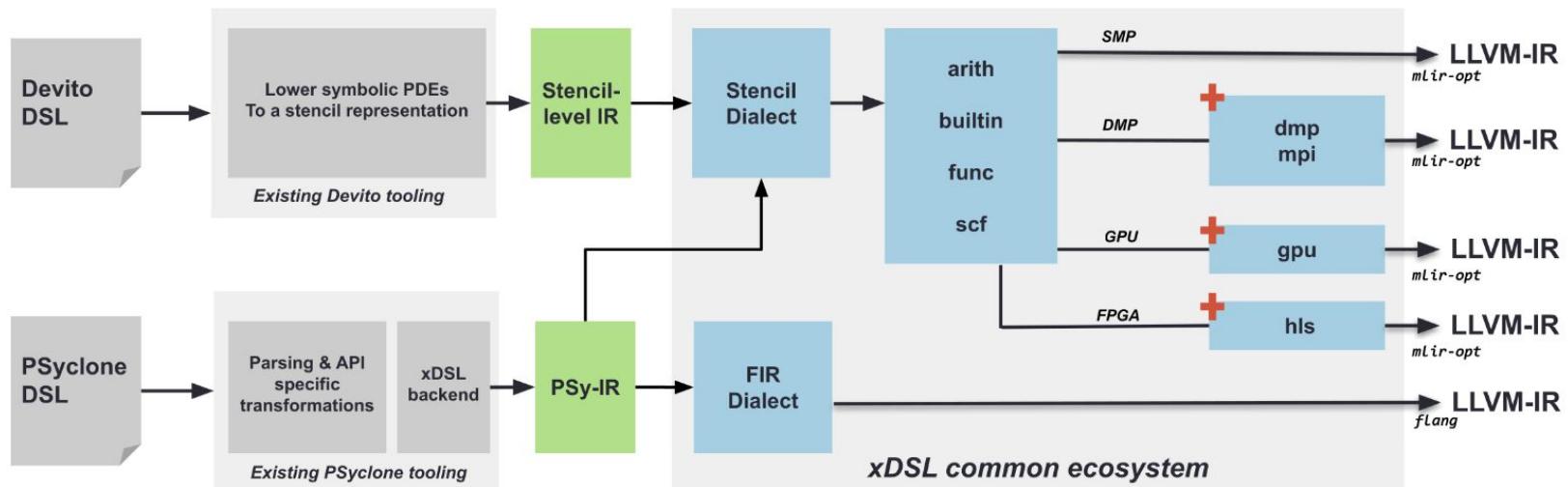
mpi.finalize() : () -> ()
```

- Simplify default constant arguments
- Out argument becomes SSA result
- Pointer + Size + Datatype = memref

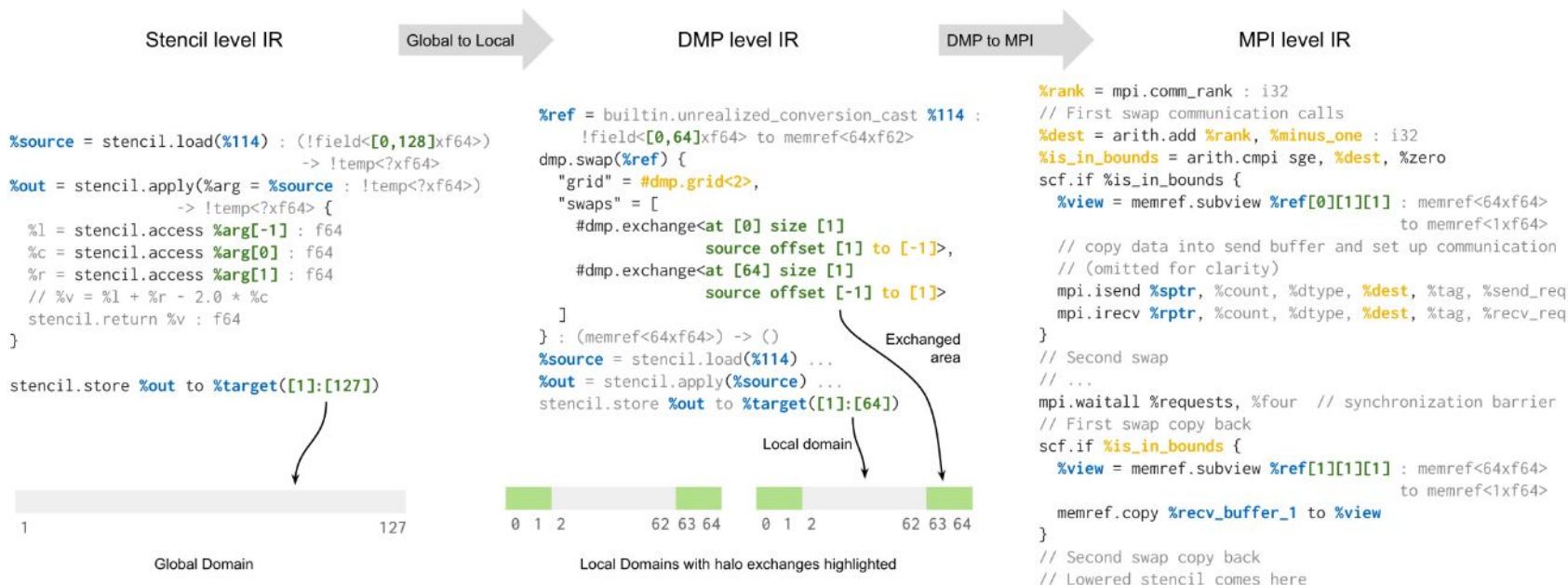
# Devito and PSYCLONE on xDSL/MLIR

Cambridge, Imperial & EPCC

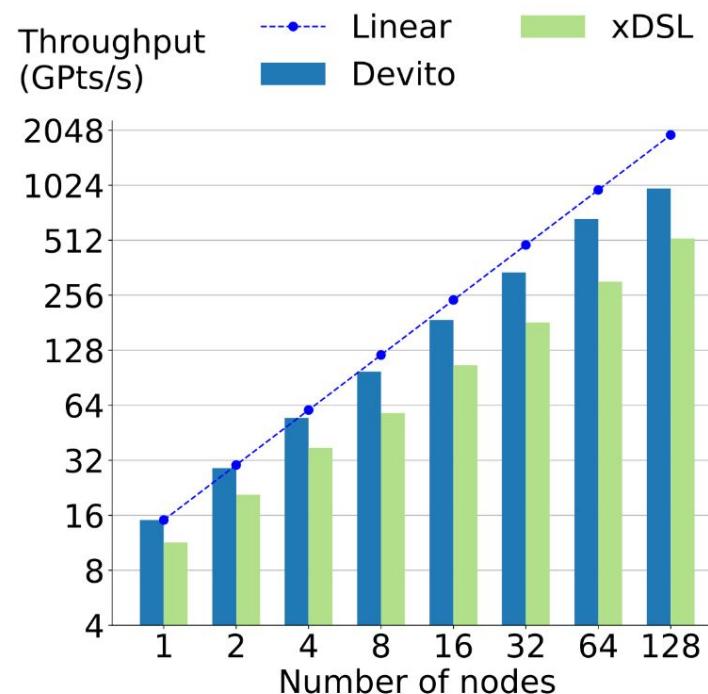
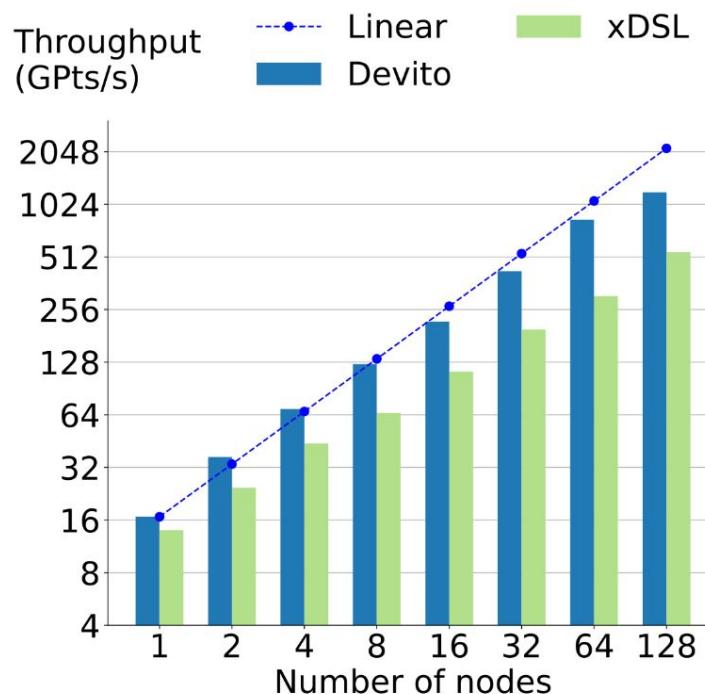
# A Joint MLIR-Based Compilation Pipeline



# From Stencils to Distributed MPI

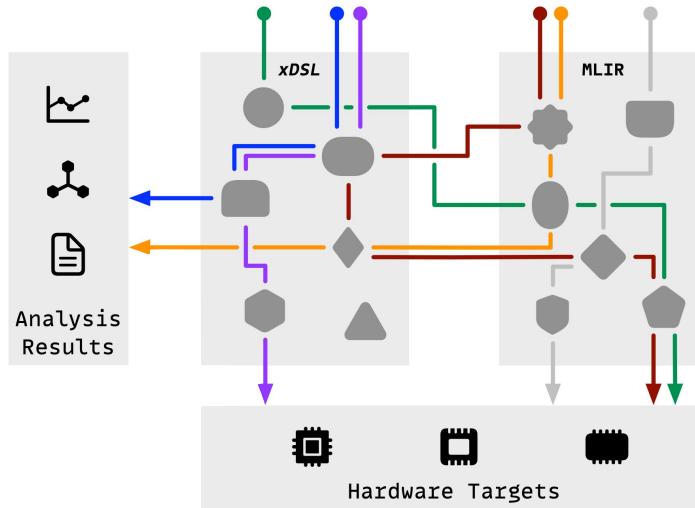


# Scalable Parallelism with xDSL/MLIR



# xDSL: A Compiler Infrastructure for DSLs

## A framework to write domain-specific compilers



<https://xdsl.dev/>

<https://github.com/xdslproject/xdsl/>

George Bisbas, Emilien Bauer, Nick Brown, Théo Degioanni, Mathieu Fehr,  
Gerard Gorman, Tobias Grosser, Paul Kelly, Sasha Lopoukhine, Martin Lücke,  
Anton Lydike, George Mitenkov, Michel Steuwer, Larisa Stoltzfus, Christian Ulmann,  
Alexander Viand, Michel Weber, ...