

GENERATING EFFICIENT CPU CODE WITH MLIR

Scalable Vector Extensions in an end-to-end case study

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DATA-TILED MATRIX MULTIPLICATIONS ARE IMPLEMENTED ON LINALG-LEVEL IN MLIR

Matmul in MLIR

```
%matmul = linalg.matmul
  ins(%lhs, %rhs : tensor<4x4xf32>,
       tensor<4x4xf32>)
  outs(%acc : tensor<4x4xf32>) ->
    tensor<4x4xf32>
```

$$\begin{array}{|c|c|c|c|} \hline 1 & 2 & 3 & 4 \\ \hline 5 & 6 & 7 & 8 \\ \hline 9 & 10 & 11 & 12 \\ \hline 13 & 14 & 15 & 16 \\ \hline \end{array} \times \begin{array}{|c|c|c|c|} \hline 1 & 2 & 3 & 4 \\ \hline 5 & 6 & 7 & 8 \\ \hline 9 & 10 & 11 & 12 \\ \hline 13 & 14 & 15 & 16 \\ \hline \end{array} = \begin{array}{|c|c|c|c|} \hline 1 & 2 & 3 & 4 \\ \hline 5 & 6 & 7 & 8 \\ \hline 9 & 10 & 11 & 12 \\ \hline 13 & 14 & 15 & 16 \\ \hline \end{array}$$

pack

$$\begin{array}{|c|c|c|c|} \hline 1 & 2 & 5 & 6 \\ \hline 3 & 4 & 7 & 8 \\ \hline 9 & 10 & 13 & 14 \\ \hline 11 & 12 & 15 & 16 \\ \hline \end{array} \times \begin{array}{|c|c|c|c|} \hline 1 & 5 & 2 & 6 \\ \hline 9 & 13 & 10 & 14 \\ \hline 3 & 7 & 4 & 8 \\ \hline 11 & 15 & 12 & 16 \\ \hline \end{array} = \begin{array}{|c|c|c|c|} \hline 1 & 2 & 5 & 6 \\ \hline 3 & 4 & 7 & 8 \\ \hline 9 & 10 & 13 & 14 \\ \hline 11 & 12 & 15 & 16 \\ \hline \end{array}$$



Data-tiled Matmul in MLIR

```
%packed_lhs = linalg.pack %lhs ...
  inner_tiles = [2, 2] into %lhs_dest :
    tensor<4x4xf32> -> tensor<2x2x2x2xf32>
%packed_rhs = linalg.pack %rhs ...
  inner_tiles = [2, 2] into %rhs_dest :
    tensor<4x4xf32> -> tensor<2x2x2x2xf32>
%packed_acc = linalg.pack %acc ...
  inner_tiles = [2, 2] into %acc_dest:
    tensor<4x4xf32> -> tensor<2x2x2x2xf32>

%mmt4d = linalg.mmt4d ins(%packed_lhs, %packed_rhs
  : tensor<2x2x2x2xf32>, tensor<2x2x2x2xf32>)
  outs(%acc_dt : tensor<2x2x2x2xf32>)

%unpack = linalg.unpack %mmt4d
  inner_tiles = [2, 2] into %acc :
    tensor<2x2x2x2xf32> -> tensor<4x4xf32>
```

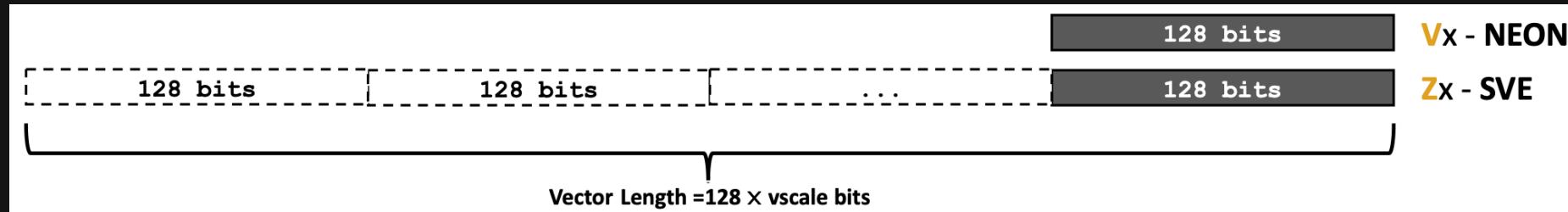
- Pack operands in a SIMD, cache-friendly layout
- Layouts dependent on target hardware
- Pack and unpack operations can be fused into their producers and consumers

INTRODUCTION

ARM'S SCALABLE VECTOR EXTENSION (SVE) ENABLES DIFFERENT VECTOR LENGTHS DECIDED BY HARDWARE IMPLEMENTATION

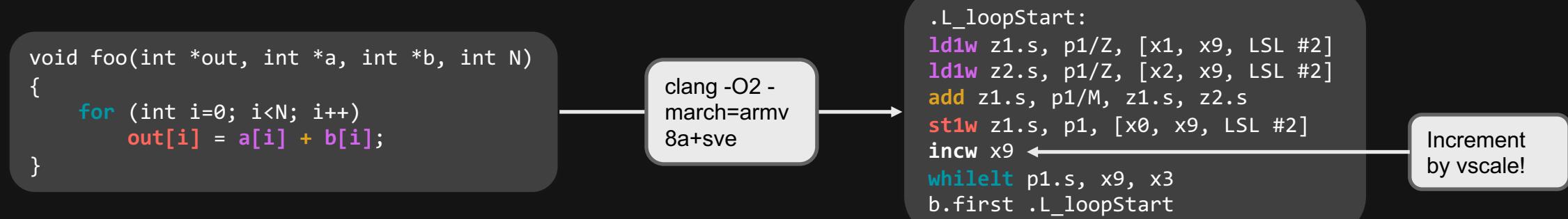
32 scalable vector registers (Z0-Z31):

- 128-2048 bits vector length is decided by implementation
- Always vscale * base size (128 bits)



ISA designed for Vector Length Agnostic (VLA) programming:

- VL (vector length) is unknown at compile-time, but known at run-time
- 16 scalable predicate registers to facilitate this (p0-p15)



INTRODUCTION

ARM'S FIXED VECTOR LENGTH EXTENSION, NEON, HAS STATIC DATA-TILED LAYOUTS

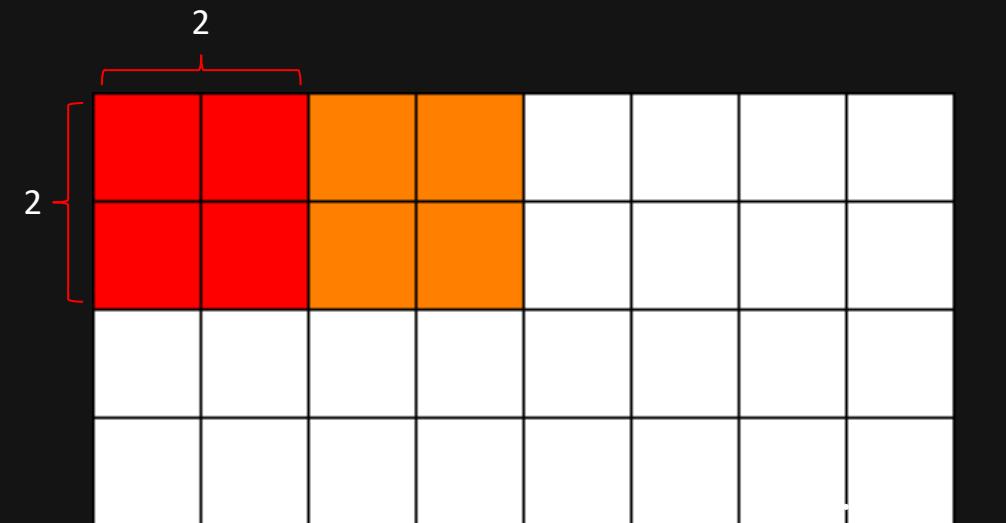
NEON overview

```
%lhs_dt = linalg.pack %lhs ...
  inner_tiles = [2, 2] into %lhs_dest :
    tensor<256x256xf32> -> tensor<128x128x2x2xf32>
%rhs_dt = linalg.pack %rhs ...
  inner_tiles = [2, 2] into %rhs_dest :
    tensor<256x128xf32> -> tensor<64x128x2x2xf32>
%acc_dt = linalg.pack %acc ...
  inner_tiles = [2, 2] into %acc_dest:
    tensor<256x128xf32> -> tensor<128x64x2x2xf32>

%mmt4d = linalg.mmt4d ins(%lhs_dt, %rhs_dt :
  tensor<128x128x2x2xf32>, tensor<64x128x2x2xf32>)
outs(%acc_dt : tensor<128x64x2x2xf32>)

%unpack = linalg.unpack %mmt4d ...
  inner_tiles = [2, 2] into %acc :
    tensor<128x64x2x2xf32> -> tensor<256x128xf32>
```

Static data-tiled layouts



WHEN USING SVE INSTEAD OF NEON, DATA-TILED LAYOUTS BECOME SCALABLE

SVE overview

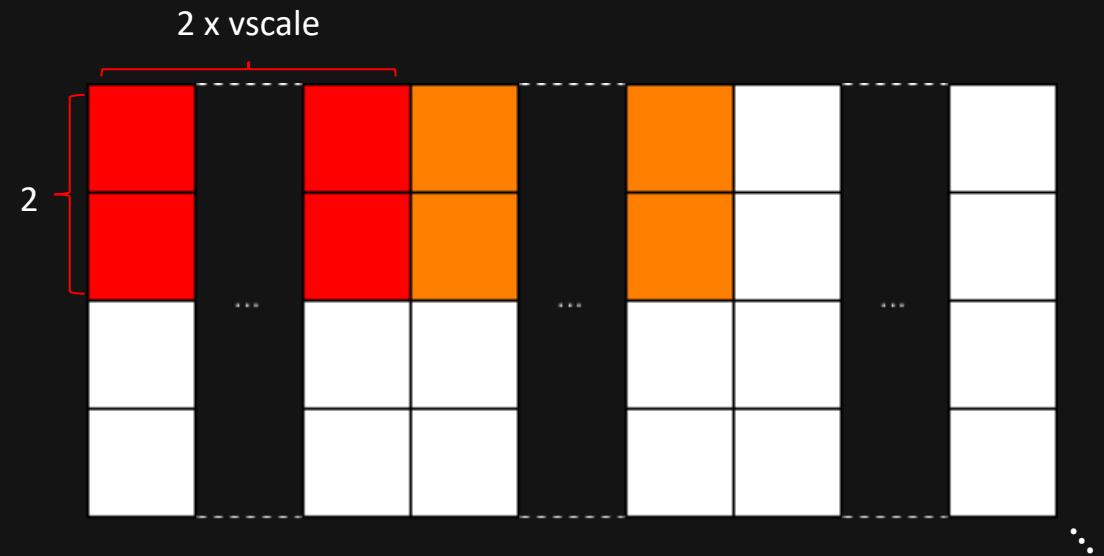
```
%vscale = vector.vscale
%c2_vscale = arith.muli %c2, %vscale : index
%packed_lhs = linalg.pack %lhs ... tensor<256x256xf32> ->
    tensor<128x128x2x2xf32>
%packed_rhs = linalg.pack %rhs ...
    inner_tiles = [%c2_vscale, 2] into %rhs_dest :
    tensor<256x128xf32> -> tensor<?x128x?x2x?f32>
%packed_acc = linalg.pack %acc
    inner_tiles = [2, %c2_vscale] into %acc_dest:
    tensor<256x128xf32> -> tensor<128x?x2x?x?f32>

%mmt4d = linalg.mmt4d ins(%packed_lhs, %packed_rhs :
    tensor<128x128x2x2xf32>, tensor<?x128x?x2x?f32>)
    outs(%packed_acc : tensor<128x?x2x?x?f32>)

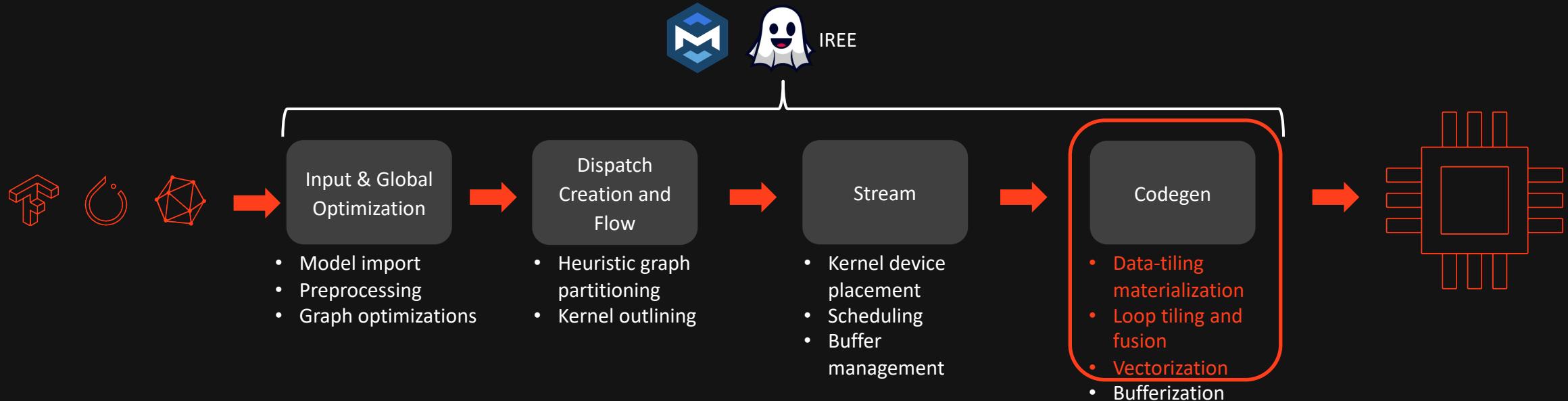
%unpack = linalg.unpack %mmt4d ...
    inner_tiles = [2, %c2_vscale] into %acc :
    tensor<128x?x2x?x?f32> -> tensor<256x128xf32>
```

Scalable tiles!

Scalable (dynamic) data-tiled layouts!



WE USE IREE AS THE UNDERLYING COMPILER INFRASTRUCTURE FOR OUR END-TO-END CASE STUDY

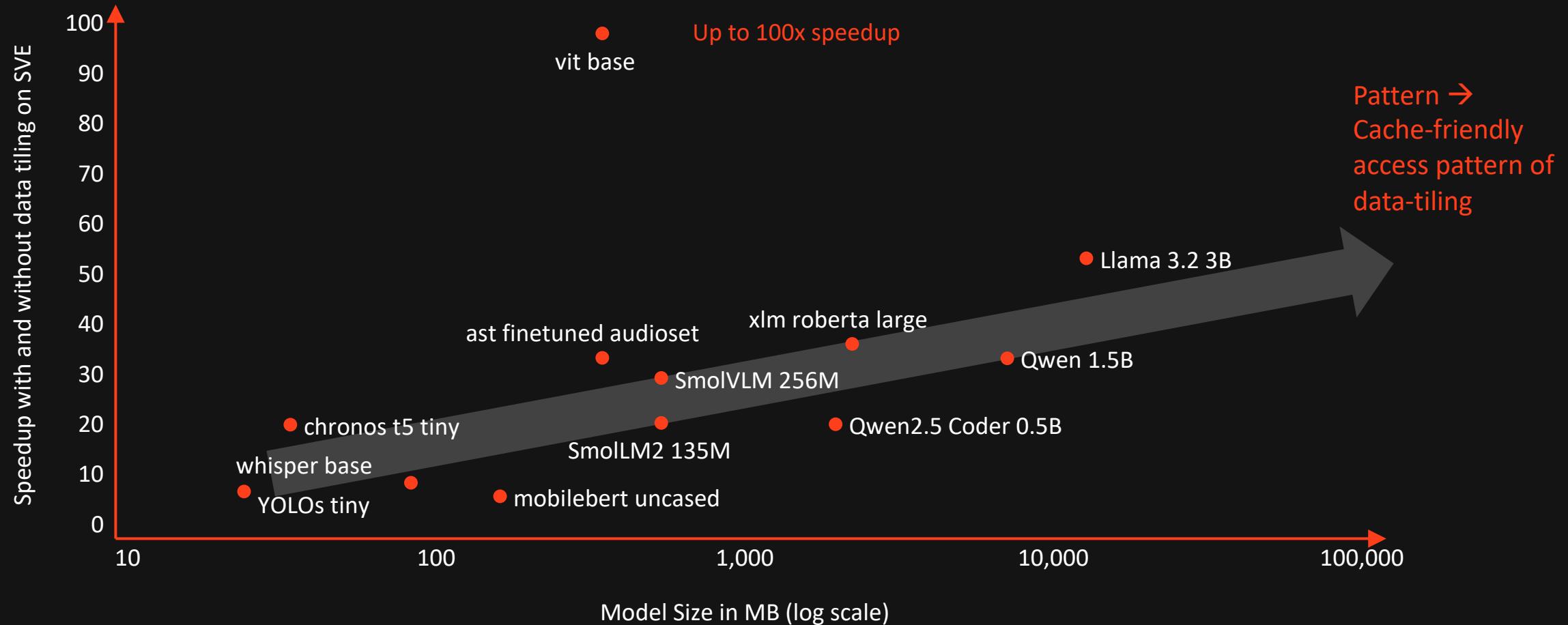


Our contribution:

- Data-tiling:** Scalable tile size selection and materialization
- Tiling and fusion:** Aligned scalable data-tiled layouts with tile sizes and tiling interfaces
- Vectorization:** Scalable vectorization of data-tiled operations

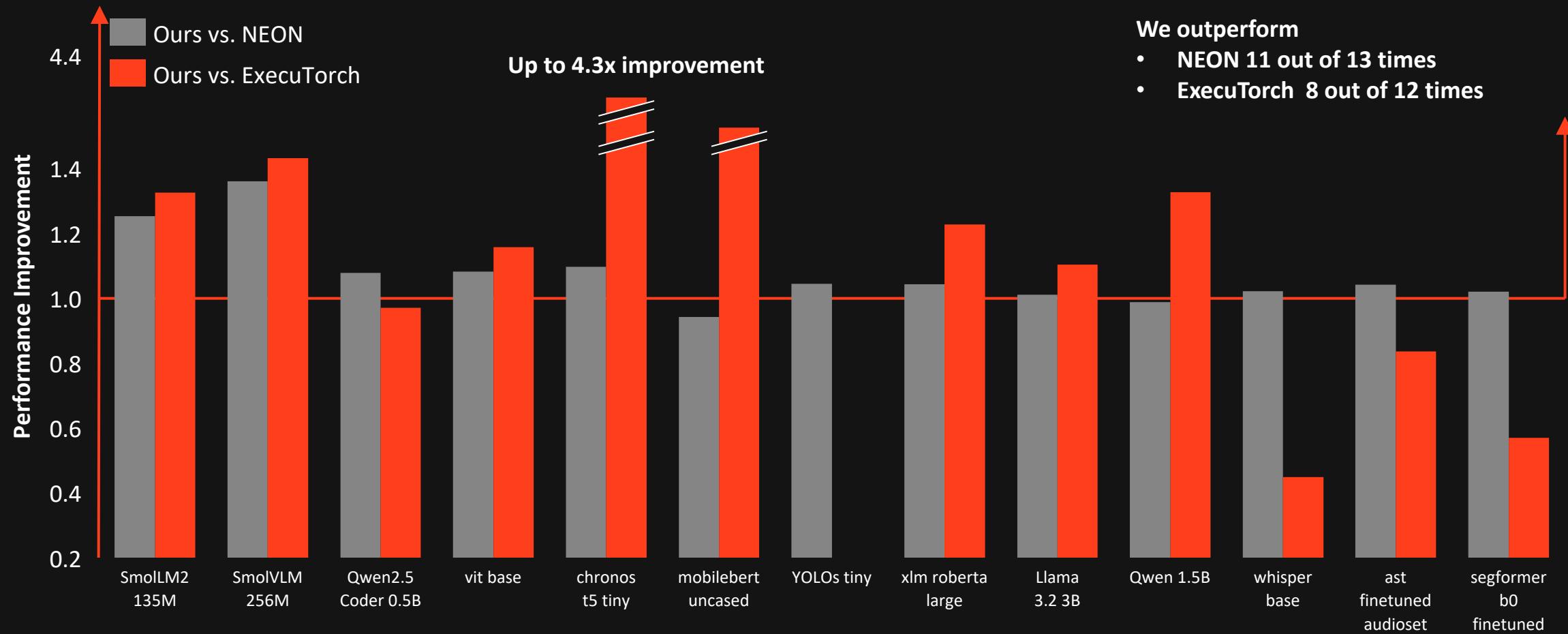
RESULTS

COMPARING DATA-TILED AND NON-DATA-TILED SVE CODE, WE FIND THAT THE SPEEDUP IS LINKED TO THE MODEL SIZE



RESULTS

COMPARING OUR SVE CODE WITH EXISTING SOLUTIONS, WE OUTPERFORM NEON AND EXECUTORCH FOR MANY LLMS



Please note: Benchmarks from Orion O6 board, with 128-bit vector length (same as NEON), FP32 weights

WE ENABLED DATA TILING FOR SCALABLE VECTOR EXTENSION, IMPROVING THE PERFORMANCE BY UP TO 4.3X

What we achieved

- ✓ Promising performance on FP32 workloads
- ✓ Little overhead from scalable vectors
- ✓ Supports Arm BF16 and I8MM extensions
- ✓ Extendable for similar architectures

What we're working on

- ❑ Not all functionality in upstream MLIR/IREE yet
- ❑ Arm BF16 and I8MM performance needs further improvements
- ❑ Extend to Arm Scalable Matrix Extension (SME) and RISC-V Vector extension