Vector Reshapes

MLIR Open Design Meeting December 14th, 2023

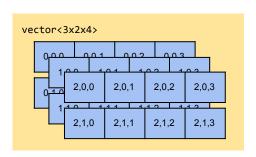
Quinn Dawkins (<u>qdawkins@amd.com</u>) with help from others

Goals of this presentation

- Focusing on a few questions and defining the problems
 - How should we think about virtual vectors?
 - What do reshapes mean on vectors?
 - O How is this related to SPIR-V?
- Primarily to understand the problem, not provide concrete proposals
- Expecting follow up RFCs and/or ODMs
 - Time permitting: Layout & SIMT

What is a virtual vector?

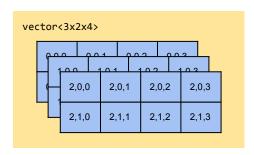
- Before discussing op semantics, how do we define the builtin <u>VectorType</u>
 - Specifically in the context of the vector dialect, other clients can do whatever they want
- <u>Docs</u> describe it as a "nested aggregate type of 1-D vector" when lowering to LLVM
 - Alternatively "stacks" of 1-D vectors
 - The inner-most size is the 1-D vector width
 - All vectors are expected to be "unrolled" to 1-D eventually



https://mlir.llvm.org/docs/Dialects/Builtin/#vectortype

What is a virtual vector?

- For accelerators with native k-D vectors, the natural extension is a "stack" of k-D vectors
- For example, a stack of 2-D vectors of the same vector shape



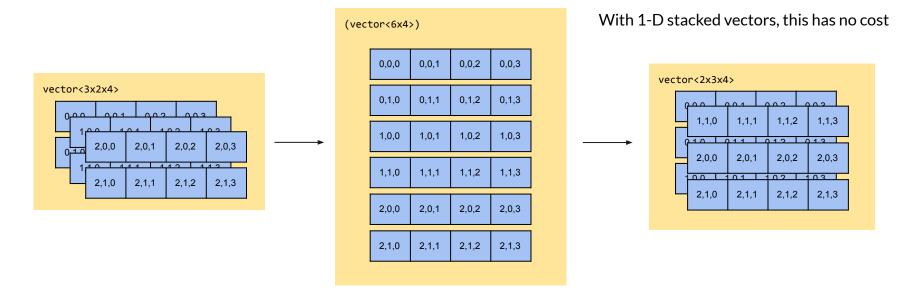
What is a virtual vector?

- Based on the current documentation, the most general interpretation does not imply any sort of native dimensionality
- Interpret it is as the data residing in a virtual SIMD register of infinite width and dimensionality
 - Vector type maps elements to locations in a virtual element space (i.e. virtual register)
- Any operation that changes the linearized bitvector, or locations of elements in the vector has cost (until a lowering asserts otherwise)

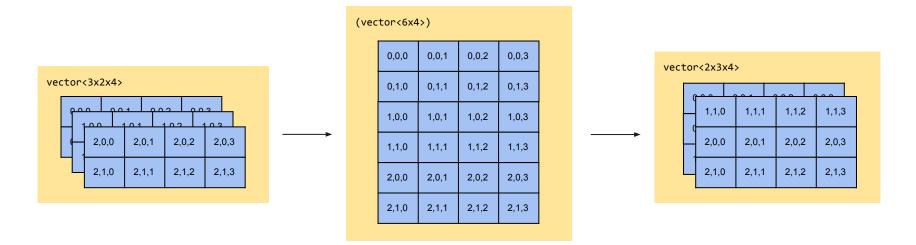
vector<3x5xi32>:

Vir	tual Re	egister																				
	0,0	0,1	0,2	0,3	0,4		 						 		 	 	 	 	 		 	
	1,0	1,1	1,2	1,3	1,4		 															
	2,0	2,1	2,2	2,3	2,4		 	i — — - 			 			i — — — · 				 				
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vector.shape_cast %0 : vector<3x2x4> to vector<2x3x4>

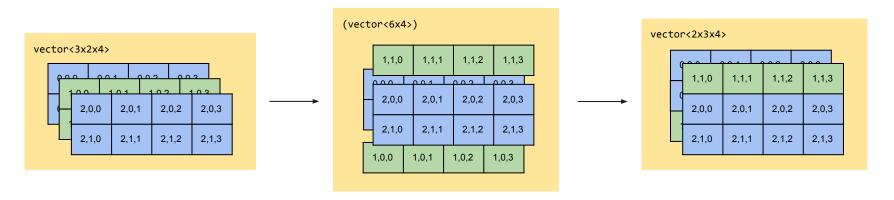


vector.shape_cast %0 : vector<3x2x4> to vector<2x3x4>



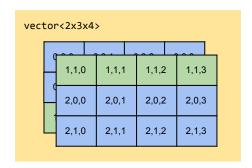
vector.shape_cast %0 : vector<3x2x4> to vector<2x3x4>

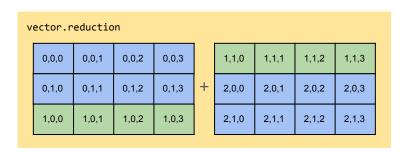
With 2-D stacked vectors, is this still a no-op?



```
%1 = vector.shape_cast %0 : vector<3x2x4> to vector<2x3x4>
```

%1 = vector.reduction <add> %1 : vector<2x3x4> to vector<3x4>

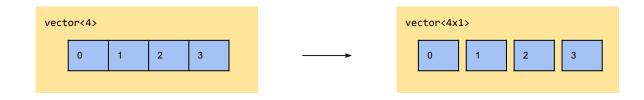




vector<3x4>											
	0,0	0,1	0,2	0,3							
	1,0	1,1	1,2	1,3							
	2,0	2,1	2,2	2,3							

vector.shape_cast %0 : vector<1x4> to vector<4x1>

Not a no-op, even with 1-D vectors



- General shape_cast is difficult to handle, especially for >1-D vector sizes
 - Many of the hardest to handle cases are likely uncommon
 - 4x1x5 -> 10x2
- Idea: "Peel off" some of the more common and easier to handle cases as different ops
 - A good litmus test for a reshape op is whether various lowering patterns would expect to handle different kinds of reshapes significantly differently

```
vector.expand_shape %0 : vector<16> to vector<4x4>
vector.collapse_shape %0 : vector<4x4> to vector<16>
```

- As identified in this <u>discourse thread</u>, unit dimensions in particular are a special case where a number of vector ops converge
 - vector.squeeze and vector.unsqueeze for reshapes only on unit dimensions

```
vector.broadcast %0 : vector<16> to vector<1x1x16>
==
vector.unsqueeze %0 : vector<16> to vector<1x1x16>
```

- As identified in this <u>discourse thread</u>, unit dimensions in particular are a special case where a number of vector ops converge
 - vector.squeeze and vector.unsqueeze for reshapes only on unit dimensions

```
vector.extract %0[0, 0] : vector<1x1x16> to vector<16>
==
vector.squeeze %0 : vector<1x1x16> to vector<16>
```

```
// No-ops for any vector dimensionality
vector.squeeze %0 : vector<1x1x16> to vector<16>
vector.unsqueeze %0 : vector<16> to vector<1x1x16>
```

- Potential cons
 - All of the reshape ops include nothing beyond type information
 - We could achieve something similar with nice matching helpers on vector.shape_cast
 - isCollapseShape
 - isExpandShape
 - isSqueeze
 - isUnsqueeze
 - Many passes + patterns will need updating to handle each of the different reshape types
 - Duplicate code unless the semantics of shape_cast are restricted

Virtual Vector -> SPIR-V

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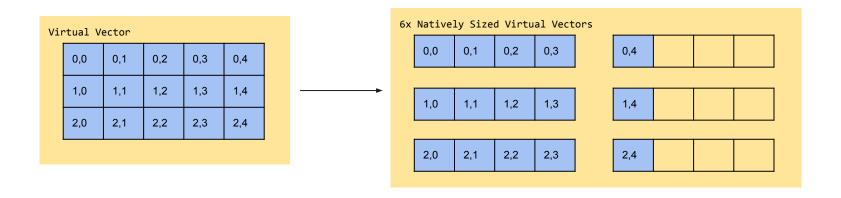
- Like LLVM, SPIR-V only supports 1-D vectors
- Additional constraint that all vectors must be <= 4 elements wide
- Currently managed with upstream unrolling patterns + canonicalization
 - SPIRVInitialVectorLowering
- Other one-off patterns for breaking down large vectors in other cases
 - o Breaking down loop carried variables
 - Breaking down other large vectors as a fallback
- Converts to memref<vector> + bitcasts to get 128 bit read/store width on < 32 bit data types
 - SPIRVVectorizeLoadStore
- Today, SPIR-V can be sensitive to small changes to canonicalizations/other vector patterns as a result
 - Goal: decouple canonicalizations and vector unrolling from target requirements

Virtual Vector -> SPIR-V

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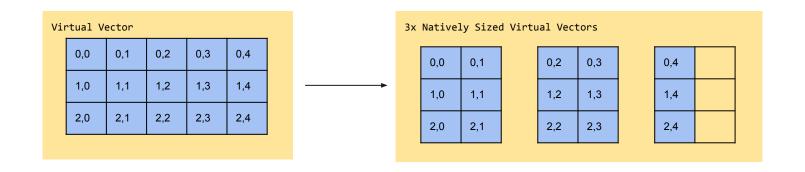
Virtual Vector -> Native Virtual Vector

- Consider the same vector<3x5xi32> mapping to 1-D hardware registers of maximum width 4
 - 6x 4-element vectors, with 3 elements masked off of 3 of the vectors



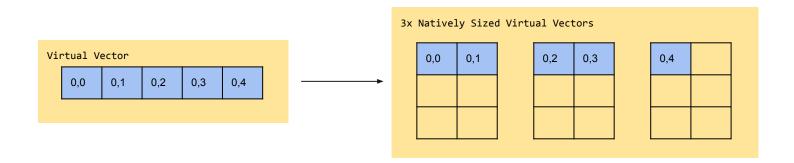
Virtual Vector -> Native Virtual Vector

• Consider the same vector<3x5xi32> mapping to 2-D vectors of shape 3x2

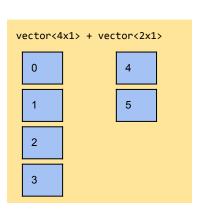


Virtual Vector -> Native Virtual Vector

- Consider vector<5xi32> mapping to 2-D hardware registers of shape 3x2
 - Masking/padding to get efficient register usage
- Could allow other partitioning schemes, this is just the most natural



```
// Always a transpose or "unshuffle to scalars"
vector.unsqueeze %0 : vector<6> to vector<6x1>
==
vector.unsqueeze %0#0 : vector<4> to vector<4x1>
vector.unsqueeze %0#1 : vector<2> to vector<2x1>
vector<4> + vector<2>
           2
```



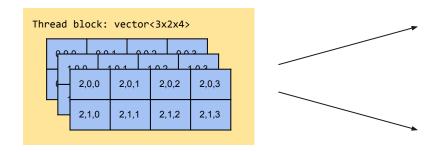
Bonus: SIMD Vector -> SIMT Vector

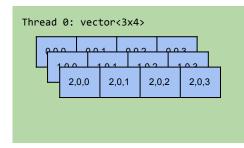
Vector vs Tensor

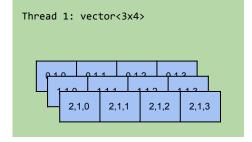
- (Ranked)TensorType
 - Value semantic "container" for some underlying data
 - Encoding attributes can be used to specify structure, otherwise there is no specific structure
 - The shape of a tensor could be metadata
- Example usage of the tensor type
 - IREE in most cases treats them simply as densely packed, contiguous bags of bytes
 - <u>Triton</u> uses tensors like a SIMD vector with a layout attribute describing how the underlying elements are held across threads, before explicitly converting to SIMT
 - https://github.com/openai/triton/blob/main/test/TritonGPU/combine.mlir
 - o In-tree efforts in the <u>sparse_tensor</u> dialect use encodings to describe various structures for how the data is stored

SIMD -> SIMT

- Even without a layout, with the above view of vectors we can still distribute
 - Implied in the rationale behind the vector dialect
 - Grid of [2] threads with an inner SIMD width of 4







Separating Distribution From Layout

- The above leaves out the analysis needed to distribute tensors/vectors
 - Separate dedicated discussion needed for layout

Summary

- Original discourse thread
 - https://discourse.llvm.org/t/improving-handling-of-unit-dimensions-in-the-vector-dialect/75216
- Defining a virtual vector in a lowering agnostic way
- Peeling off functionality from vector.shape_cast to cover a few common cases
 - o squeeze/unsqueeze for the special properties of unit dimensions
- LLVM centric vector lowerings require extra work on the SPIR-V side
 - Seeing a similar trend with the scalable vector bring-up