

Custard and The Sparse Abstract Machine: Compiling Sparse Applications to Coarse- Grained Reconfigurable Arrays

Olivia Hsu

Dataflow hardware can accelerate sparse tensor algebra

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$$\begin{aligned}
 a &= Bc + a & a &= Bc & A &= B + C \\
 a &= B^T c + d & a &= B^T c & A &= \alpha B & a &= Bc + b \\
 & & & & & & a &= b \odot c & a &= B(c + d) \\
 A &= B + C + D & A &= BC & & & A &= B \odot (CD) \\
 A &= B \odot C & A &= 0 & A &= BCd & A &= B^T & a &= B^T Bc \\
 a &= b + c & A &= B & K &= A^T C A & a &= \alpha Bc + \beta a
 \end{aligned}$$



$$\begin{aligned}
 A_{ij} &= \sum_{kl} B_{ikl} C_{lj} D_{kj} & A_{kj} &= \sum_{il} B_{ikl} C_{lj} D_{ij} \\
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 A_{ijk} &= \sum_l B_{ikl} C_{lj} & A_{ik} &= \sum_j B_{ijk} c_j \\
 A_{jk} &= \sum_i B_{ijk} c_i & A_{ijl} &= \sum_k B_{ikl} C_{kj} \\
 C &= \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}} \overline{P_{il}} & \tau &= \sum_i z_i \left(\sum_j z_j \theta_{ij} \right) \left(\sum_k z_k \theta_{ik} \right) \\
 a &= \sum_{ijklmnop} M_{ij} P_{jk} M_{kl} P_{lm} \overline{M_{nm}} \overline{P_{no}} \overline{M_{po}} \overline{P_{ip}}
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Need Generality to Handle This...

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Need Generality to Handle This...

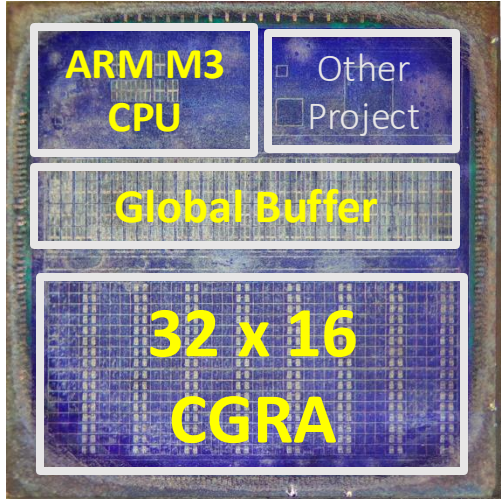
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 \end{aligned}$$



Onyx CGRA

[Koul et al. VLSI, HotChips 2024]

but really any sparse accelerator...

Need Generality to Handle This...

Performance requires generality in schedules

Performance requires generality in schedules

Fusion

Dataflow Ordering

Performance requires generality in schedules

$$A = B \odot (CD)$$

SDDMM

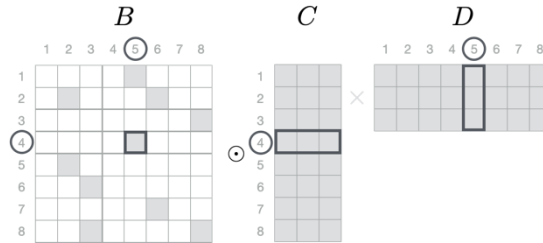
Fusion

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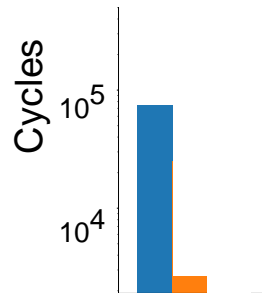
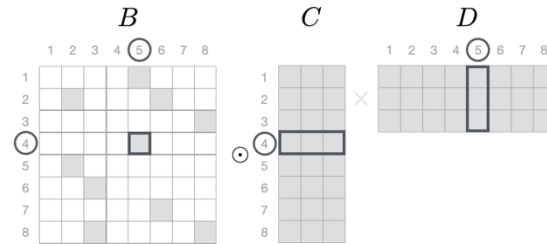
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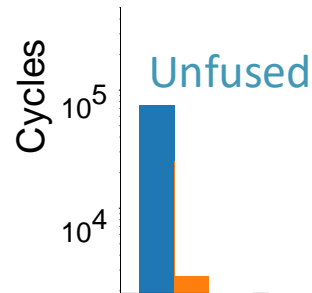
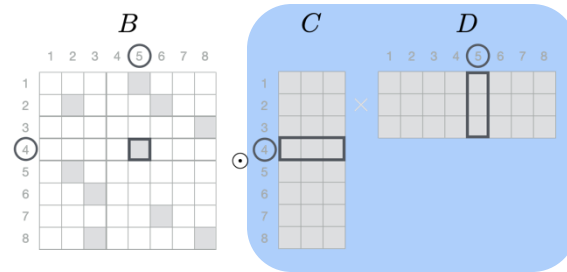
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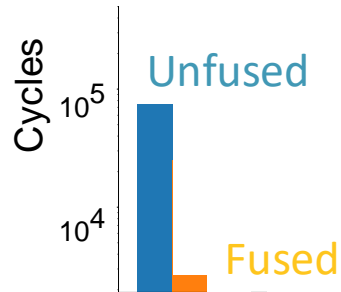
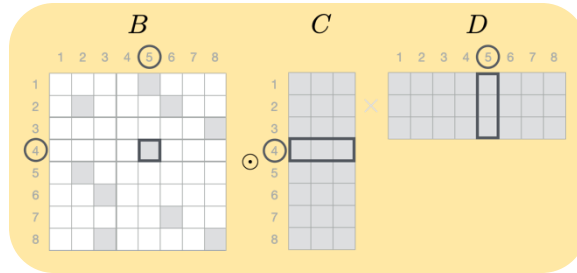
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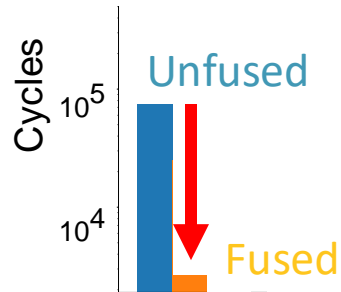
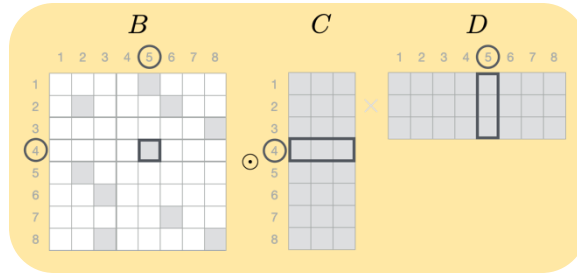
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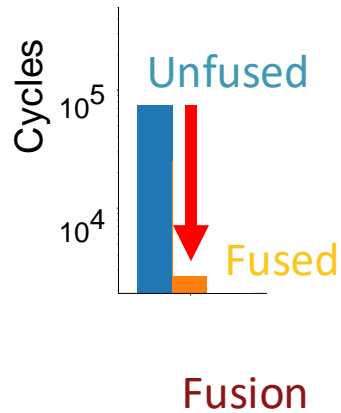
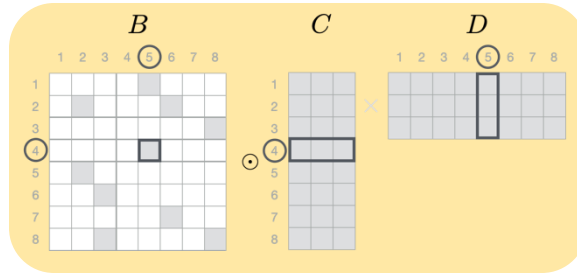
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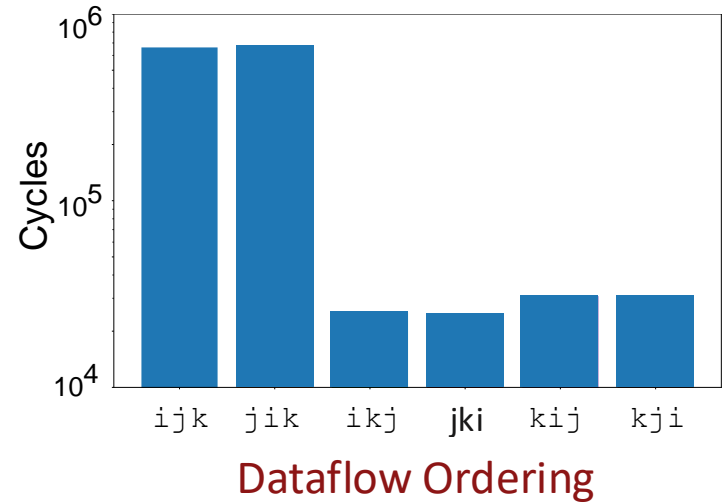
$$A = B \odot (CD)$$

SDDMM



$$X_{ij} = B_{ik} \cdot C_{kj}$$

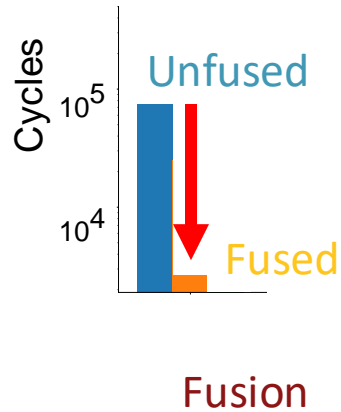
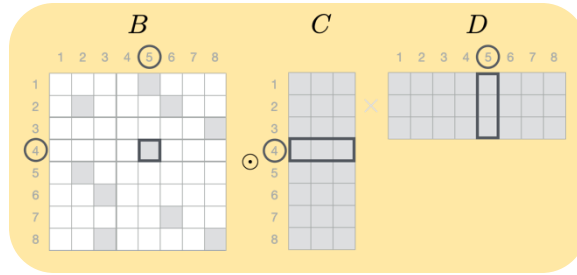
SpMSpM



Performance requires generality in schedules

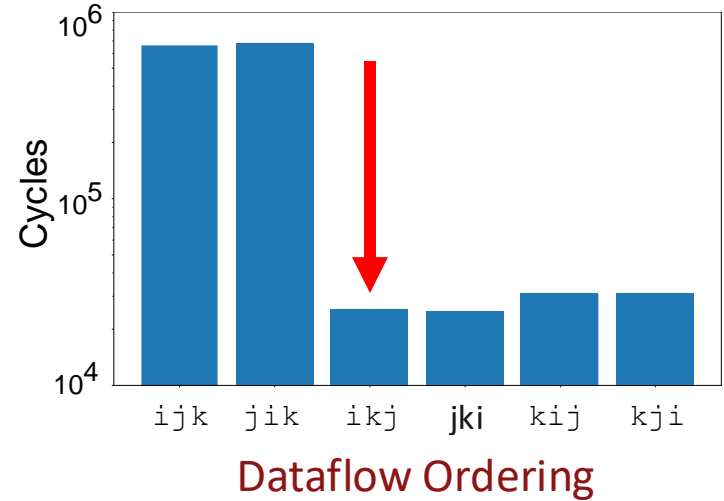
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SDDMM



$$X_{ij} = B_{ik} \cdot C_{kj}$$

SpMSpM



Efficient mapping requires a compiler

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$$\begin{aligned}
 a &= Bc + a & a &= Bc & A &= B + C & \text{Linear Algebra} \\
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 A_{ijk} &= \sum_l B_{ikl} C_{lj} & A_{ik} &= \sum_j B_{ijk} C_j & \text{Data analytics} \\
 & & & & & & & & & \text{(tensor} \\
 A_{jk} &= \sum_i B_{ijk} C_i & A_{ijl} &= \sum_k B_{ikl} C_{kj} & \text{factorization)}
 \end{aligned}$$

$$\begin{aligned}
 C &= \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}} \overline{P_{il}} & \tau &= \sum_i z_i \left(\sum_j z_j \theta_{ij} \right) \left(\sum_k z_k \theta_{ik} \right) \\
 a &= \sum_{ijklmnop} M_{ij} P_{jk} M_{kl} P_{lm} \overline{M_{nm}} \overline{P_{no}} \overline{M_{po}} \overline{P_{ip}} & & \\
 & & & & & & \text{Quantum Chromodynamics}
 \end{aligned}$$

Algorithm (expression)

Efficient mapping requires a compiler

$a = Bc + a$ $a = Bc$ $A = B + C$ Linear Algebra
 $a = B^T c + d$ $a = B^T c$ $A = \alpha B$ $a = Bc + b$
 $a = B(c + d)$
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 $a = b + c$ $A = B$ $K = A^T C A$ $a = \alpha Bc + \beta a$

$A_{ij} = \sum_{kl} B_{ikl} C_{lj} D_{kj}$ $A_{kj} = \sum_{il} B_{ikl} C_{lj} D_{ij}$
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 $A_{ijk} = \sum_l B_{ikl} C_{lj}$ $A_{ik} = \sum_j B_{ijk} c_j$ Data analytics (tensor factorization)
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$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}} \overline{P_{il}}$ $\tau = \sum_i z_i (\sum_j z_j \theta_{ij}) (\sum_k z_k \theta_{ik})$
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- reorder
- precompute
- parallelize split
- map divide
- vectorize unroll
- position

Algorithm (expression)

Schedule

Efficient mapping requires a compiler

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Algorithm (expression)



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Schedule

- EIE
- SpArch OuterSPACE
- Gamma MatRaptor
- Plasticine Sigma
- Tensaurus
- Onyx Sparse TPU
- Eyeriss V2 SCNN
- UCNN SpaceA
- Spada
- Fifer Sparse CGRAs
- SPU ExTensor
- Capstan
- ... and future

Backend

Efficient mapping requires a compiler

All of Sparse Tensor Algebra

$a = Bc + a$ $a = Bc$ $A = B + C$ $A = B \odot (C + D)$ $A = B \odot (CD)$
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$A_{ijk} = \sum_l B_{ikl} C_{lj}$ $A_{ik} = \sum_j B_{ijk} c_j$ **Data analytics (tensor factorization)**
 $A_{jk} = \sum_i B_{ijk} c_i$ $A_{ijl} = \sum_k B_{ikl} C_{kj}$

$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}} \overline{P_{il}}$ $\tau = \sum_i z_i (\sum_j z_j \theta_{ij}) (\sum_k z_k \theta_{ik})$
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Algorithm (expression)



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$a_j = \sum_{kl} B_{ikl} C_{lj} D_{kj}$ $A_{kj} = \sum_{il} B_{ikl} C_{lj} D_{ij}$
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Algorithm (expression)



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Schedule

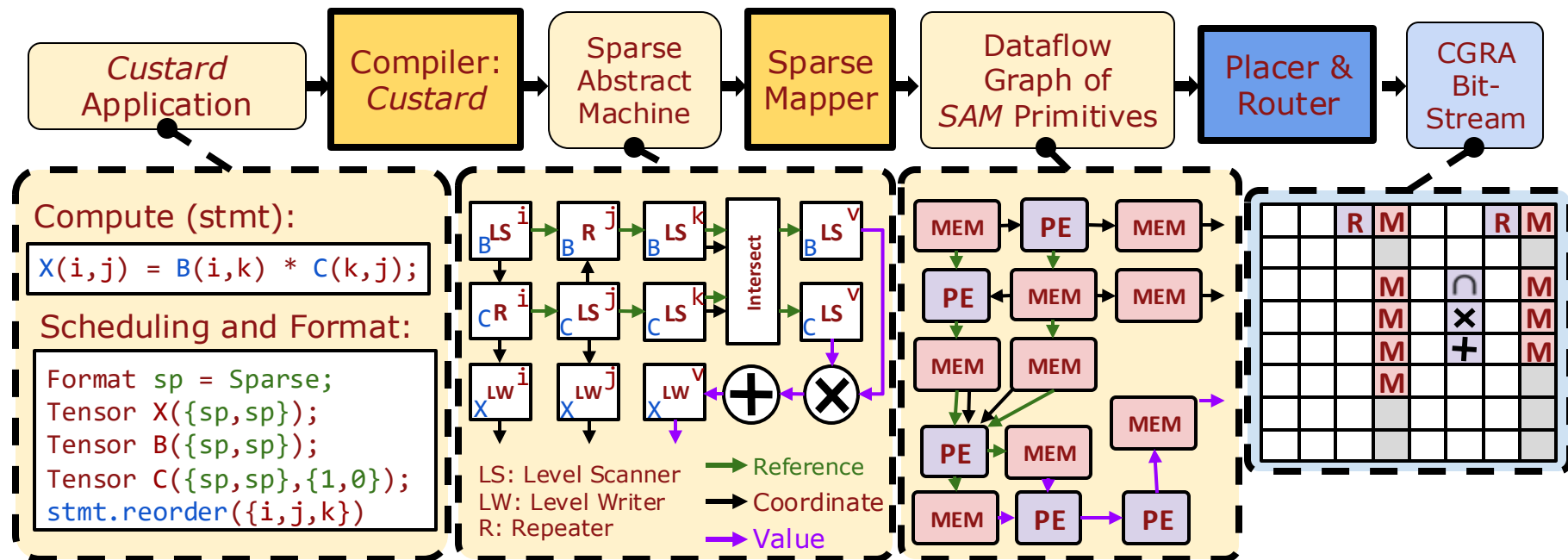


Lends itself to multiple backends

- MatRaptor
- Sigma
- Onyx Sparse TPU
- SCNN
- Eyeriss V2
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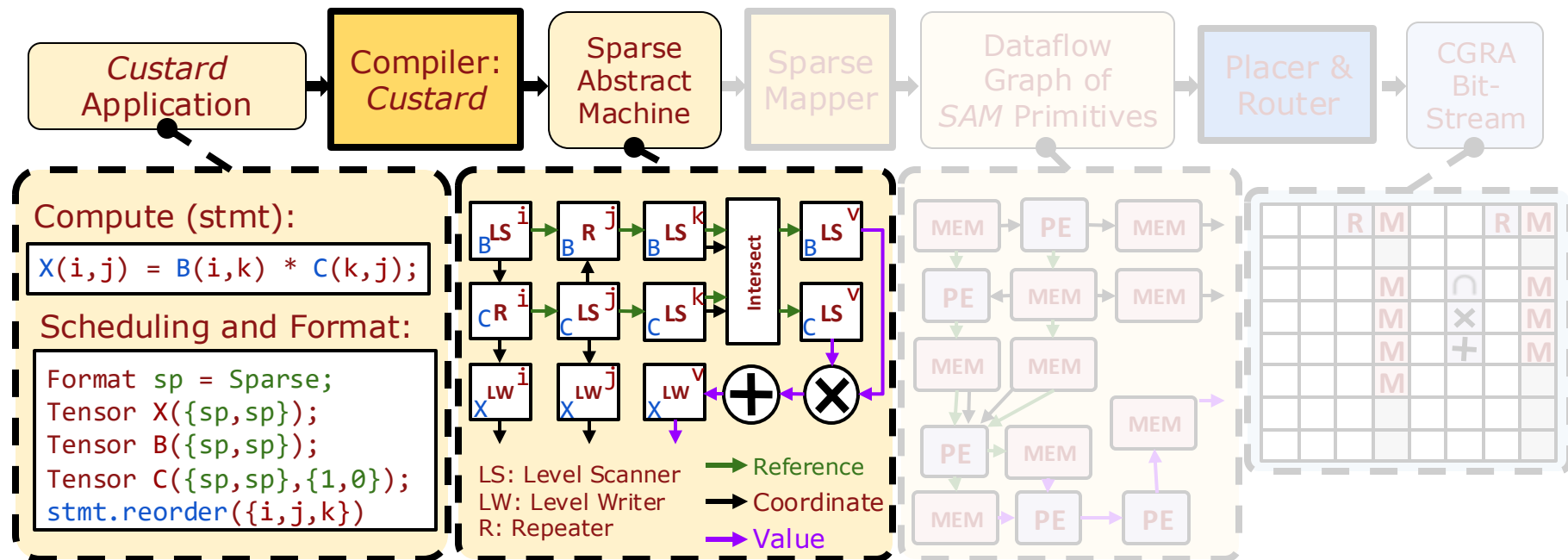
Backend

This work in the DSL-based CGRA flow

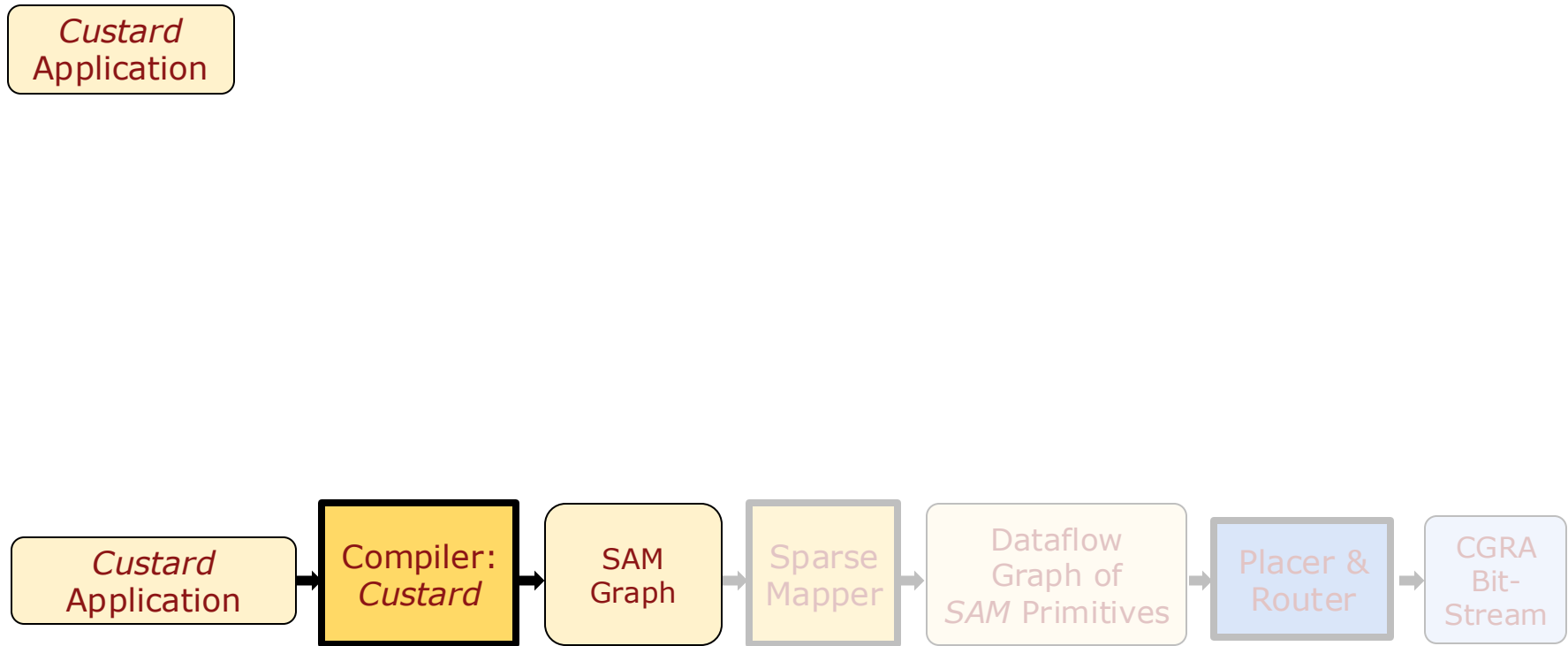


This work in the DSL-based CGRA flow

[Hsu et al. ASPLOS 2023]



SAM leverages domain-specific languages and comes with the Custard compiler

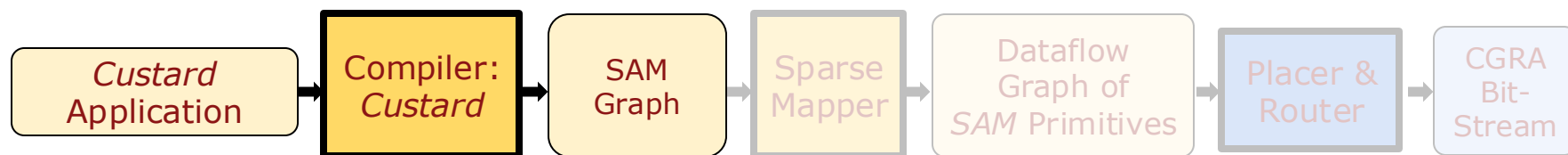


SAM leverages domain-specific languages and comes with the Custard compiler

Custard
Application

```
X(i,j) = B(i,k) * C(k,j);
```

Tensor Index
Notation



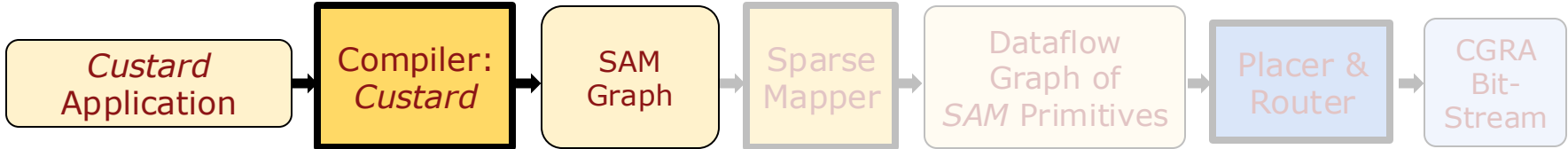
SAM leverages domain-specific languages and comes with the Custard compiler

Custard
Application

```
Format sp = Sparse;  
Tensor X({sp,sp});  
Tensor B({sp,sp});  
Tensor C({sp,sp},{1,0});  
  
X(i,j) = B(i,k) * C(k,j);
```

Formats

Tensor Index
Notation

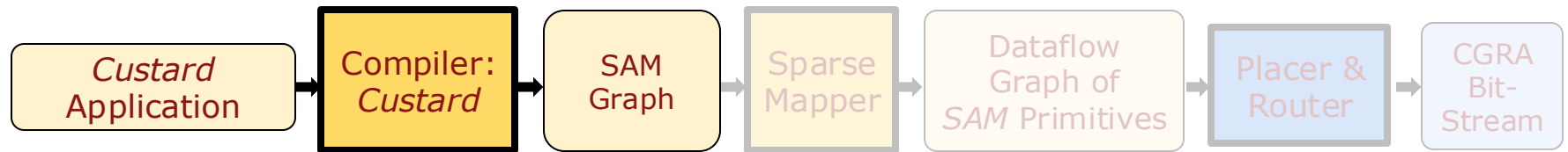


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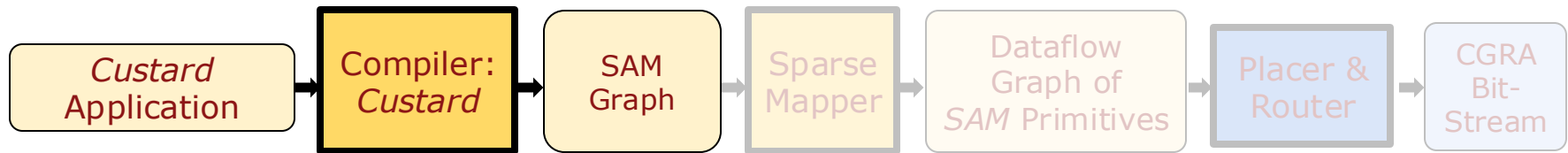
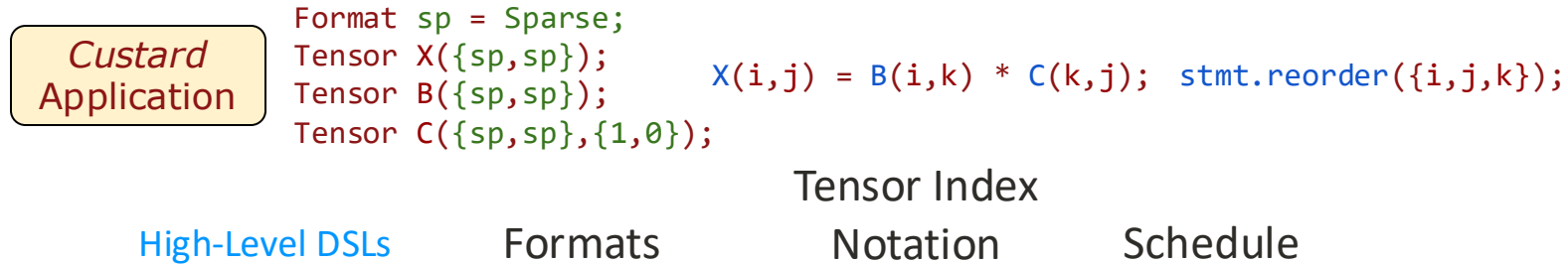
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Tensor B({sp,sp});  
Tensor C({sp,sp},{1,0});  
  
X(i,j) = B(i,k) * C(k,j); stmt.reorder({i,j,k});
```

Formats Tensor Index Notation Schedule

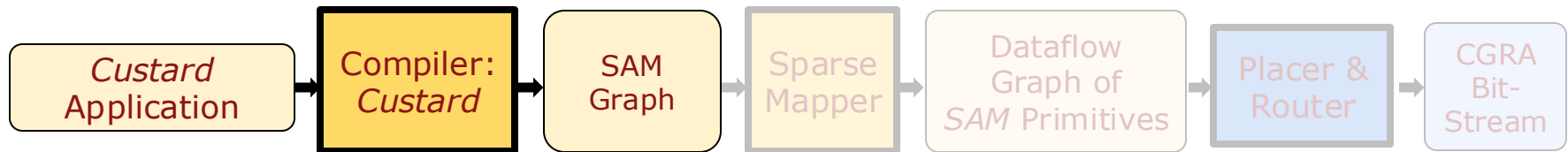
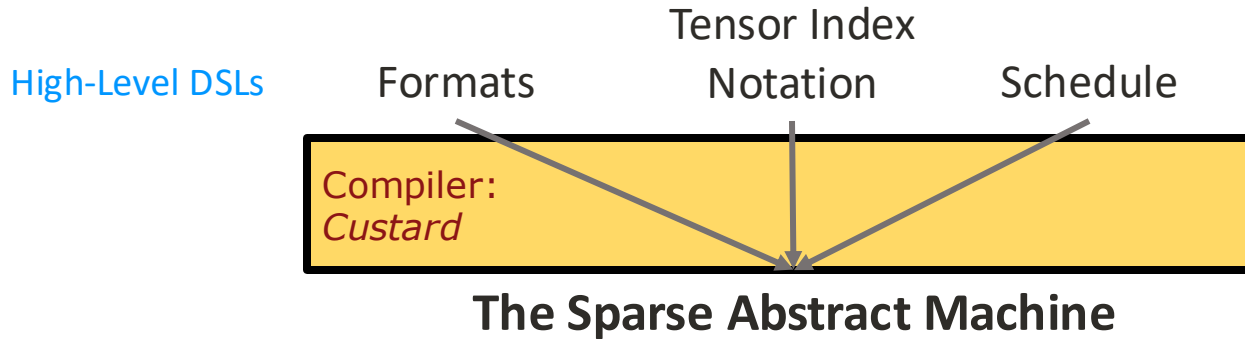


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SAM leverages domain-specific languages and comes with the Custard compiler

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Custard Application
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Representing dataflow in SAM

SAM represents:

1. Wires carrying data through streams
2. Modules that compute on the data through primitives

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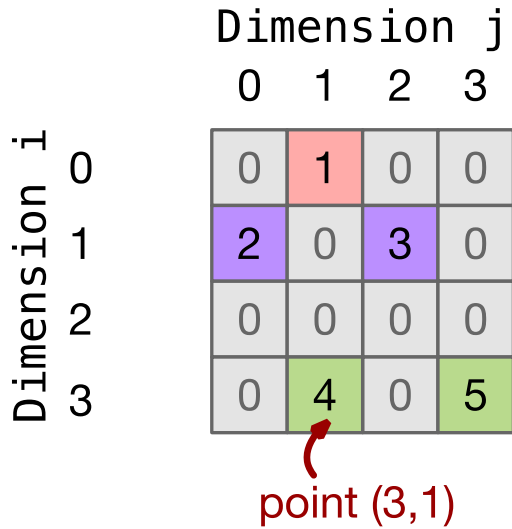
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1. Wires carrying data through streams
2. Modules that compute on the data through primitives



Representing tensors in SAM



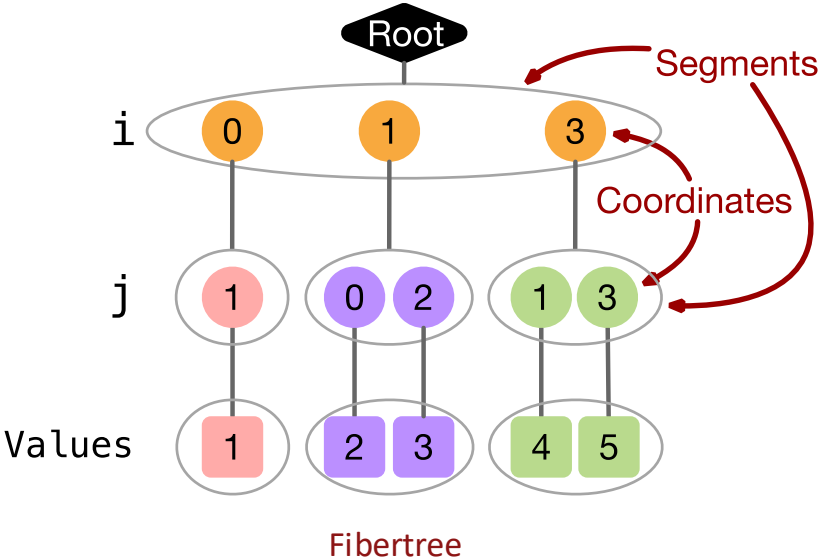
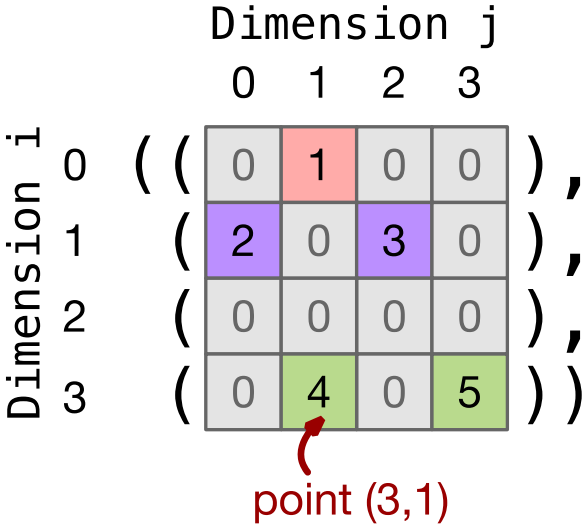
Representing tensors in SAM

Dimension j

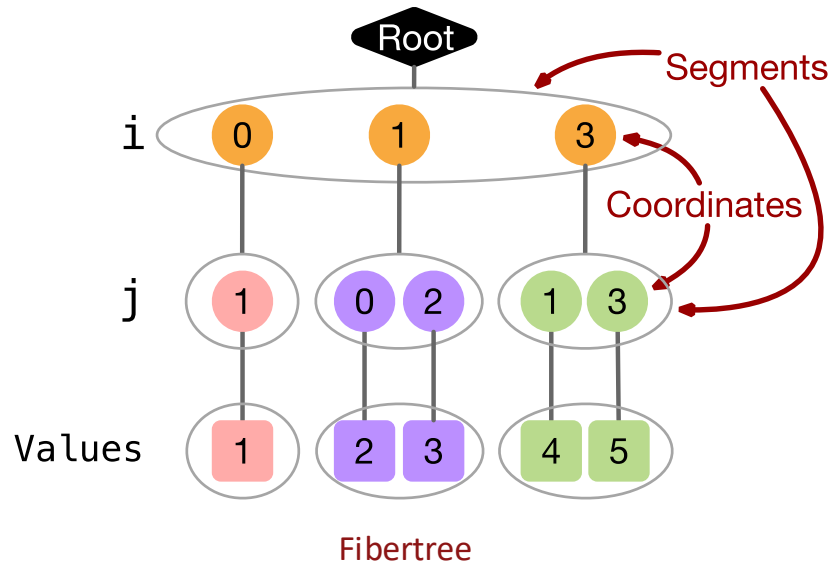
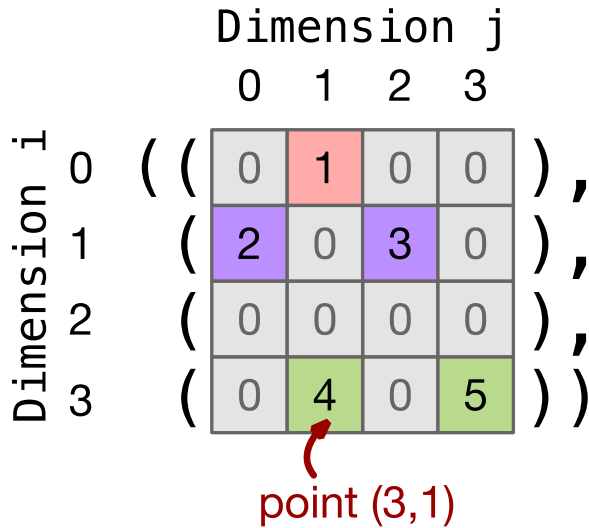
	0	1	2	3
Dimension i 0	((0 1 0 0) ,			
1	((2 0 3 0) ,			
2	((0 0 0 0) ,			
3	((0 4 0 5))			

point (3,1)

Representing tensors in SAM



Representing tensors in SAM



(0, 1, 3)

((1), (0, 2), (1, 3))

((1), (2, 3), (4, 5))

As data structures and flattened streams

(0, 1, 3)

((1), (0, 2), (1, 3))

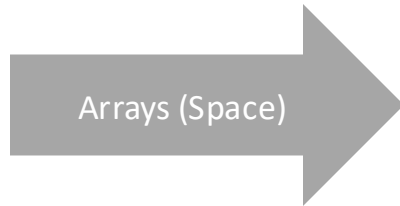
((1), (2, 3), (4, 5))

As data structures and flattened streams

(0, 1, 3)

((1), (0, 2), (1, 3))

((1), (2, 3), (4, 5))

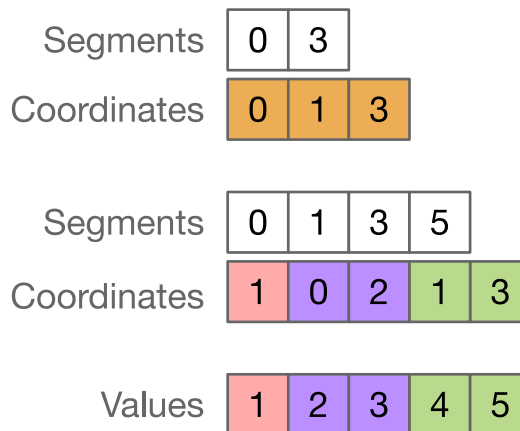
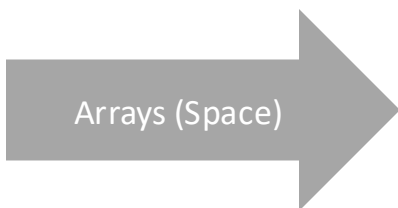


As data structures and flattened streams

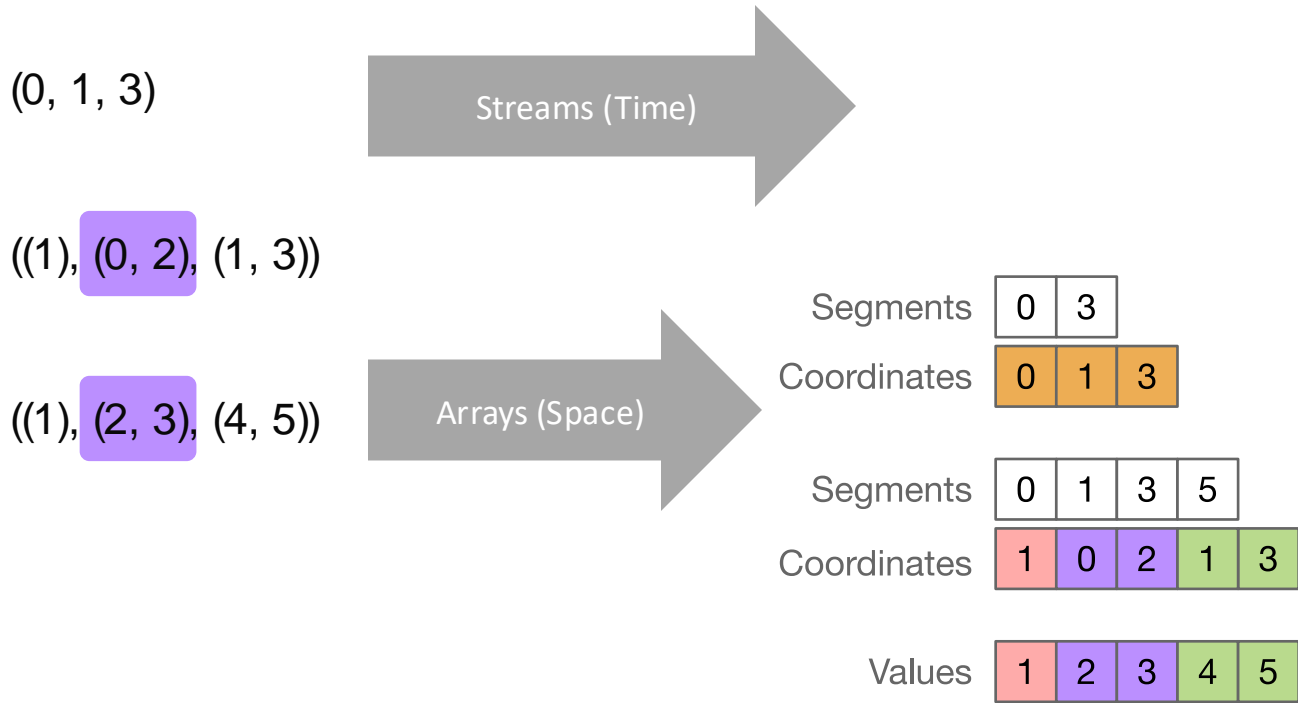
(0, 1, 3)

((1), (0, 2), (1, 3))

((1), (2, 3), (4, 5))



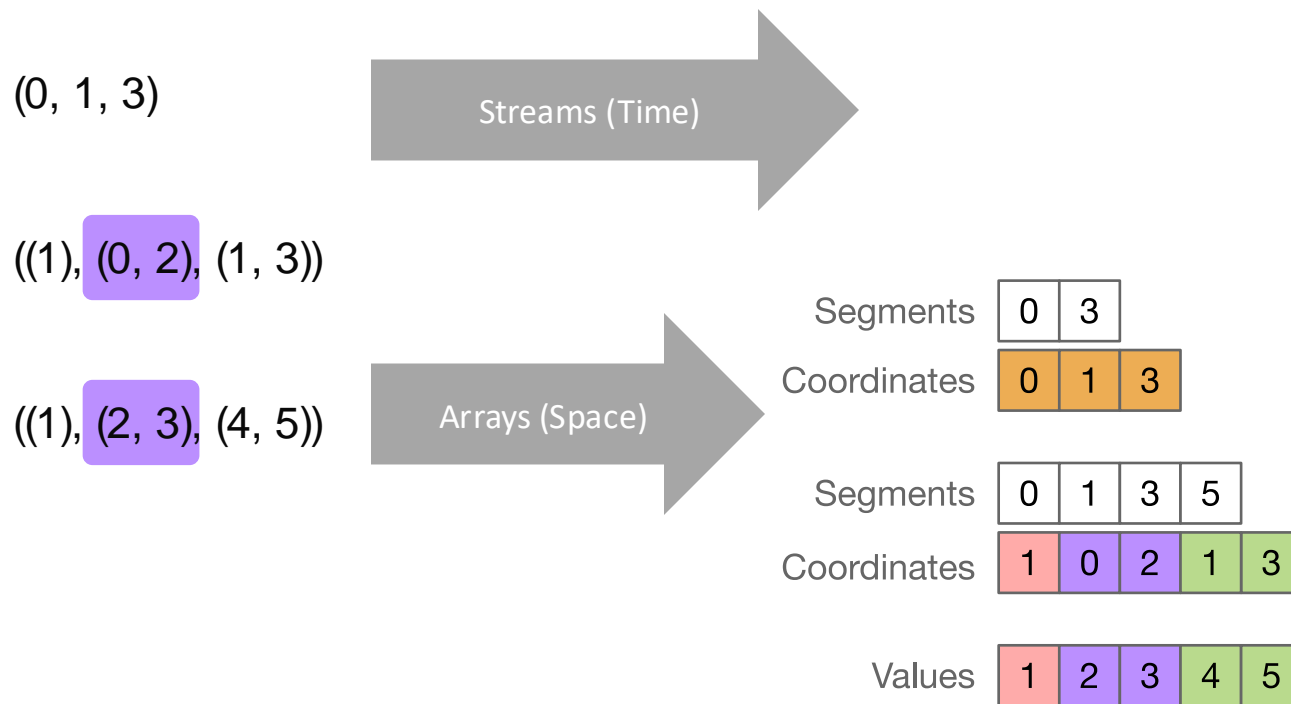
As data structures and flattened streams



As data structures and flattened streams

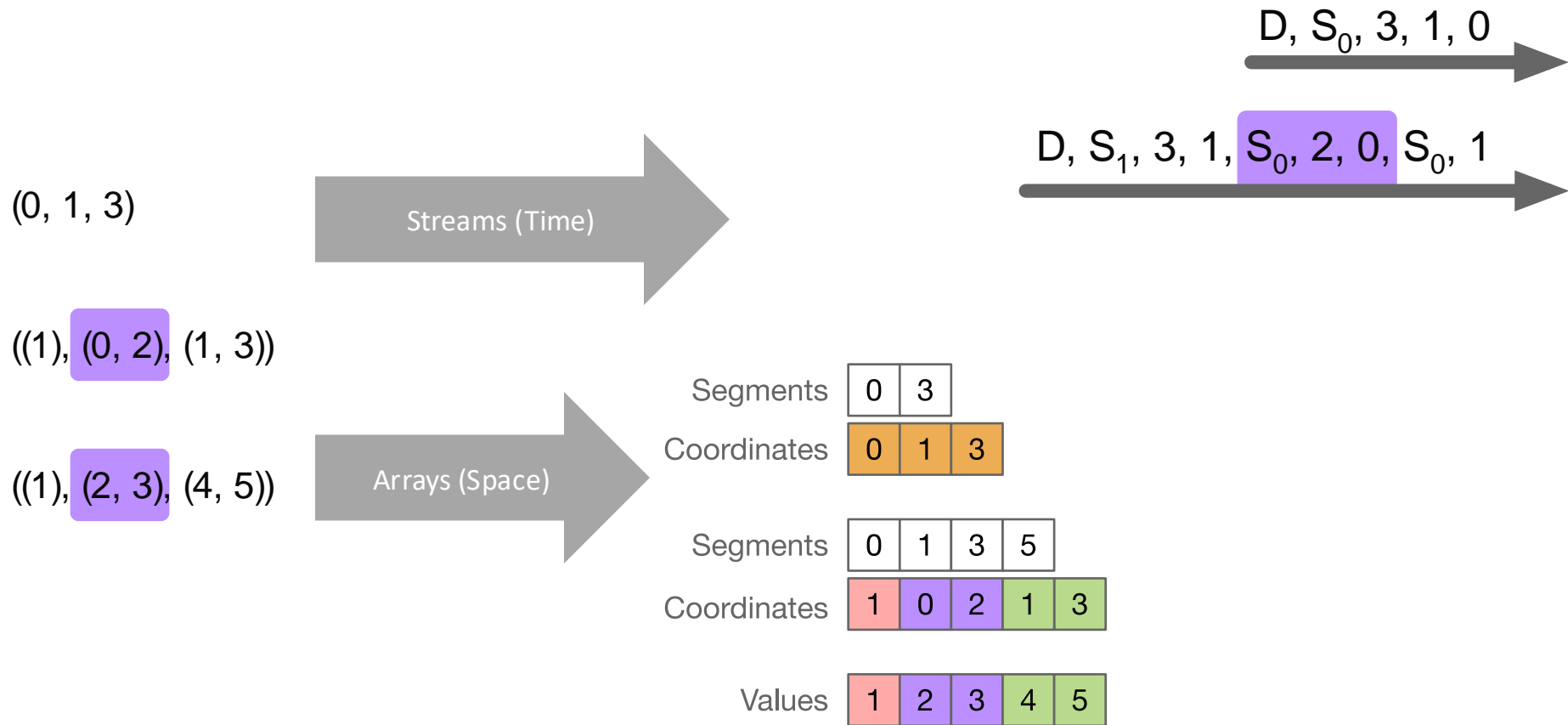
SAM
Graph

D, S₀, 3, 1, 0



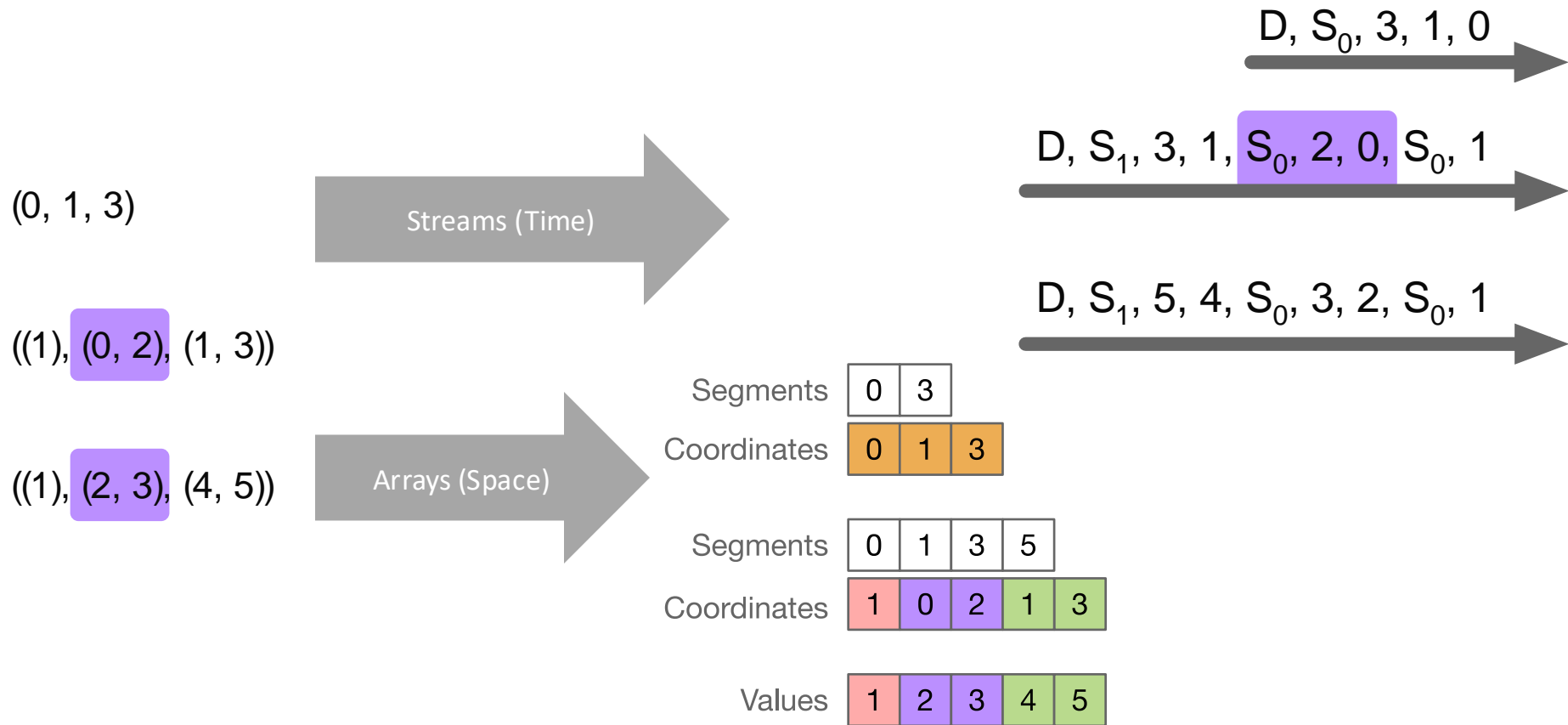
As data structures and flattened streams

SAM Graph



As data structures and flattened streams

SAM Graph



As data structures and flattened streams

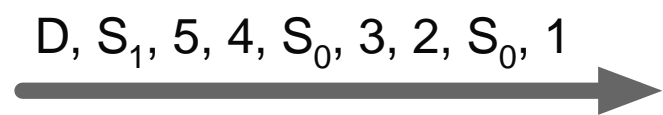
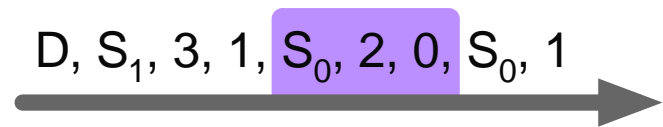
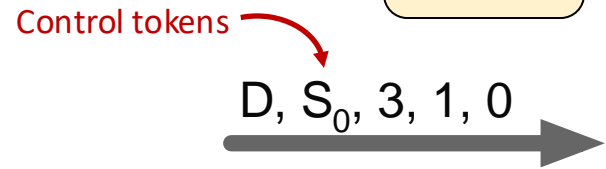
SAM Graph



((1), (0, 2), (1, 3))



Segments	0	3			
Coordinates	0	1	3		
Segments	0	1	3	5	
Coordinates	1	0	2	1	3
Values	1	2	3	4	5



SAM supports all of tensor algebra

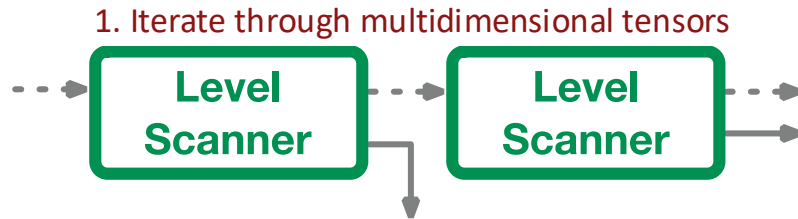
SAM
Graph

The sparse abstract machine has clean interfaces defined for each feature of sparse tensor algebra, called primitives

SAM supports all of tensor algebra

SAM
Graph

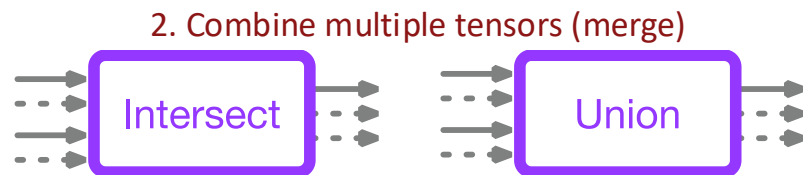
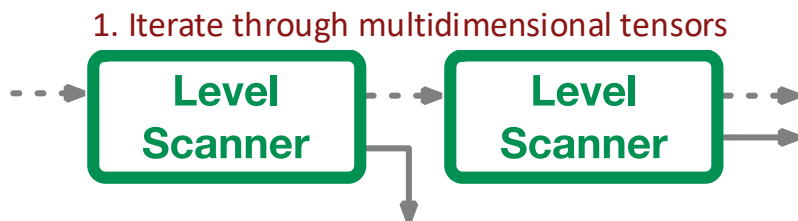
The sparse abstract machine has clean interfaces defined for each feature of sparse tensor algebra, called primitives



SAM supports all of tensor algebra

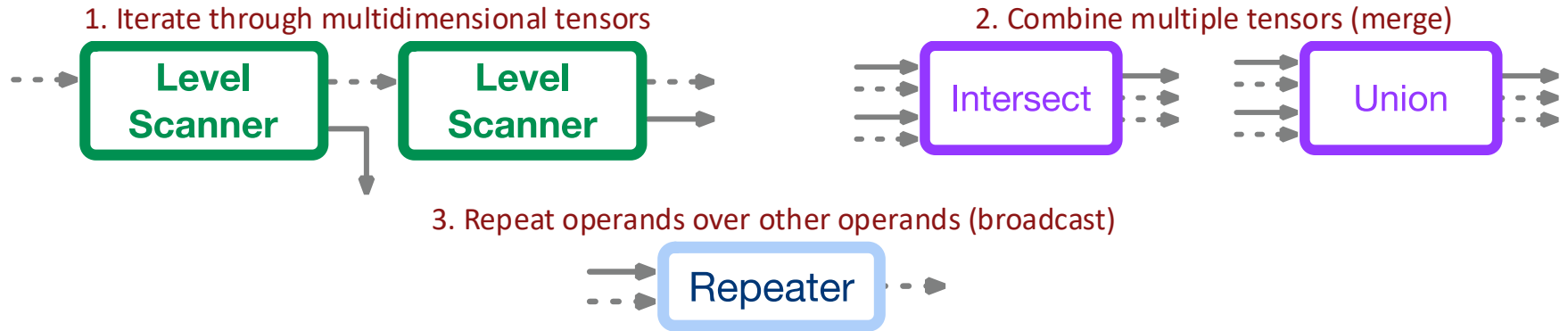
SAM
Graph

The sparse abstract machine has clean interfaces defined for each feature of sparse tensor algebra, called primitives



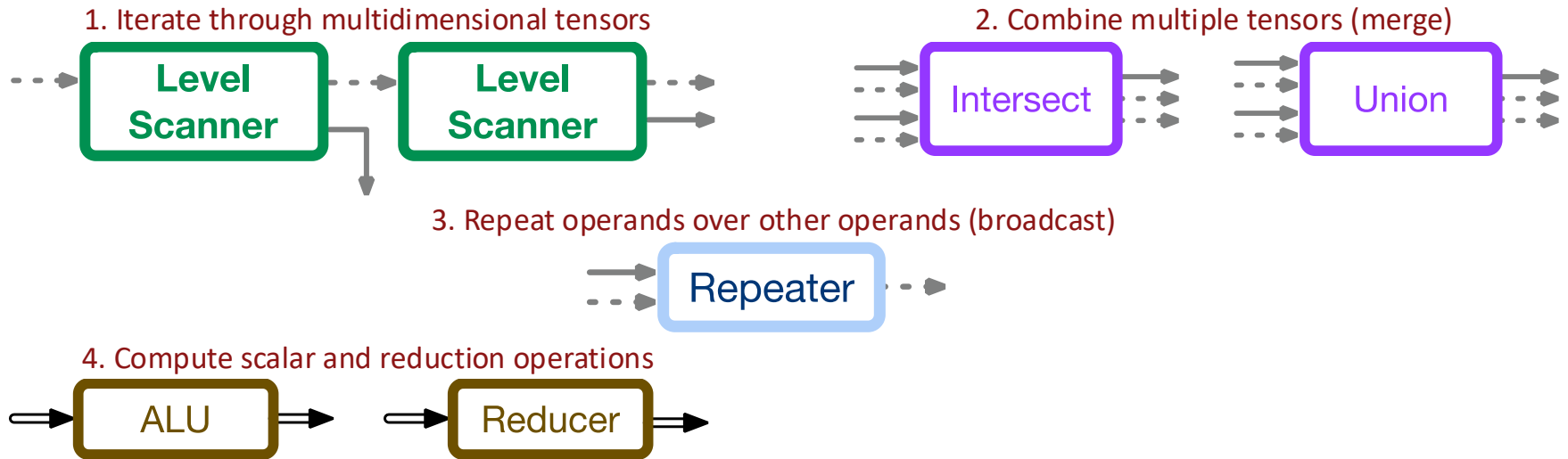
SAM supports all of tensor algebra

The sparse abstract machine has clean interfaces defined for each feature of sparse tensor algebra, called primitives



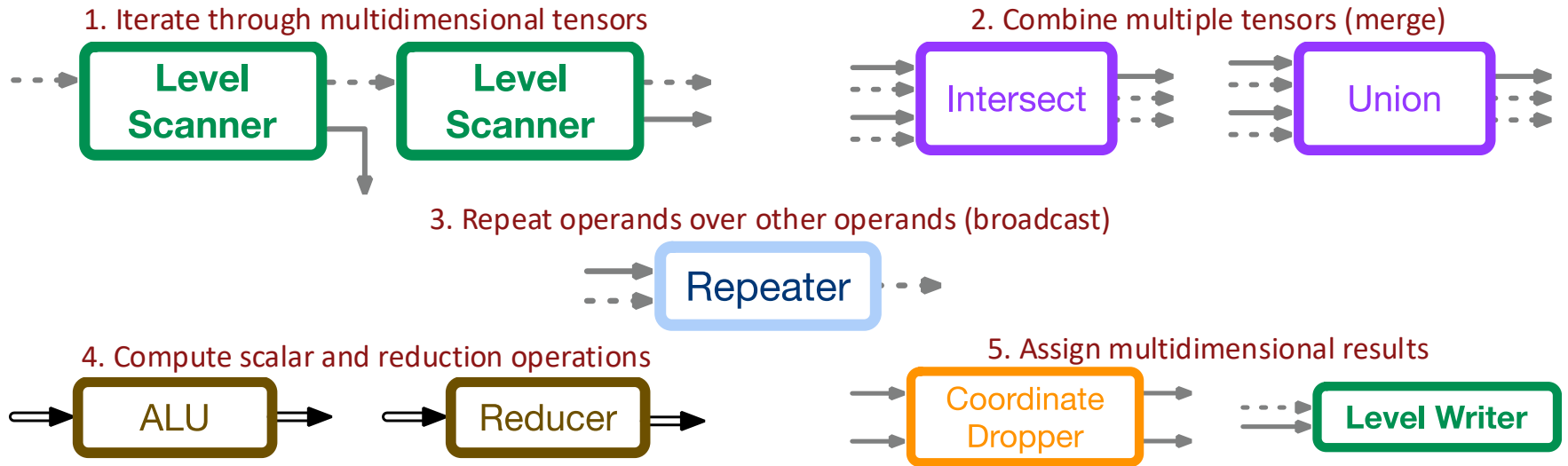
SAM supports all of tensor algebra

The sparse abstract machine has clean interfaces defined for each feature of sparse tensor algebra, called primitives



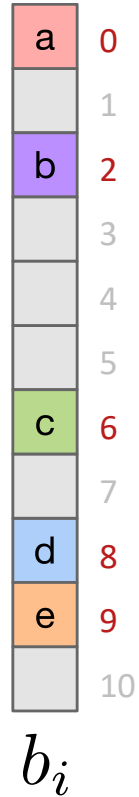
SAM supports all of tensor algebra

The sparse abstract machine has clean interfaces defined for each feature of sparse tensor algebra, called primitives



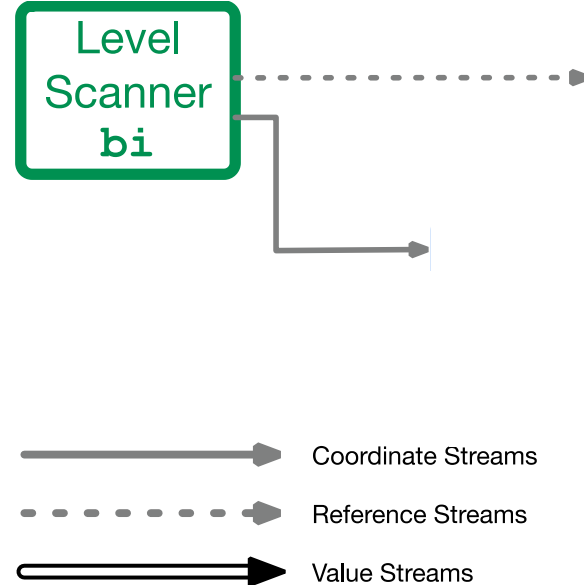
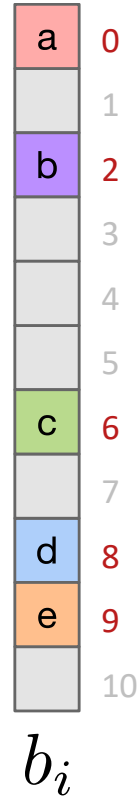
Vector scaling example with repeaters

$$x_i = \underline{b_i} \cdot c$$



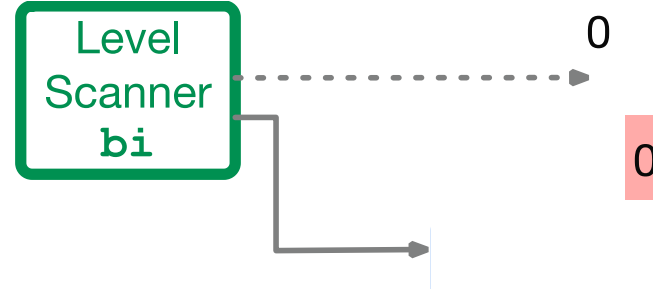
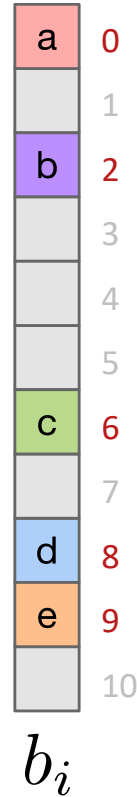
Vector scaling example with repeaters




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Vector scaling example with repeaters

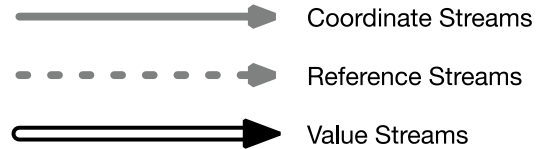
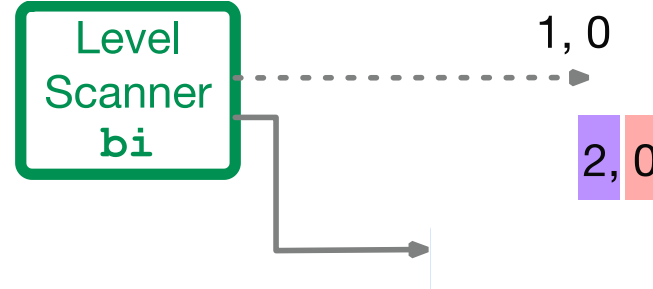
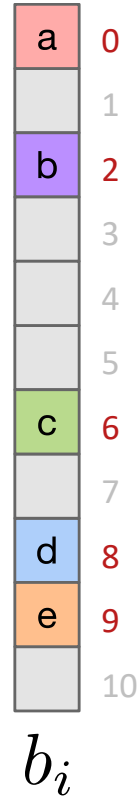
$$x_i = \underline{b_i} \cdot c$$



-  Coordinate Streams
-  Reference Streams
-  Value Streams

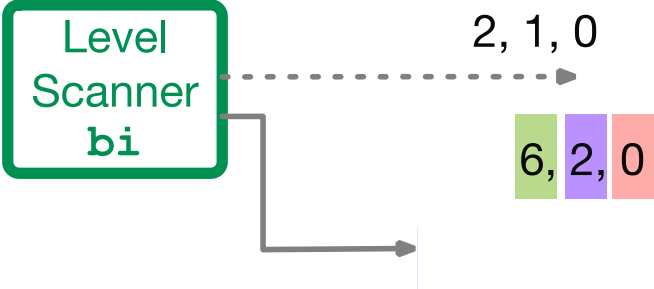
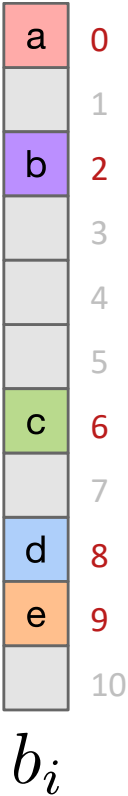
Vector scaling example with repeaters

$$x_i = \underline{b_i} \cdot c$$



Vector scaling example with repeaters

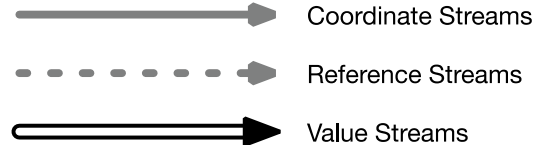
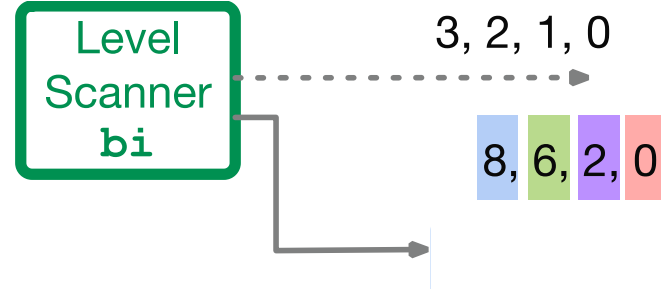
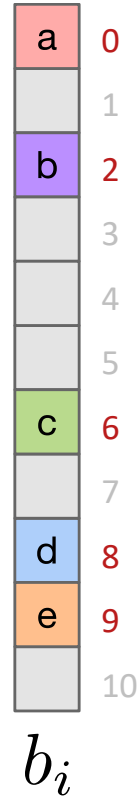
$$x_i = \underline{b_i} \cdot c$$



- Coordinate Streams
- Reference Streams
- Value Streams

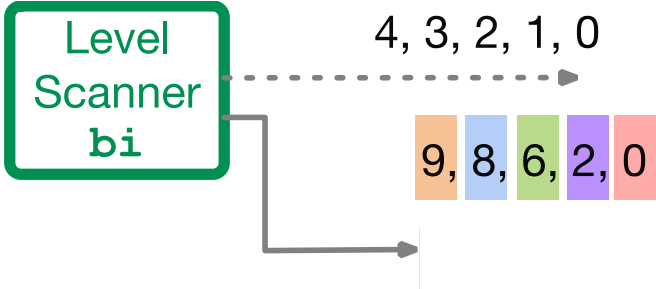
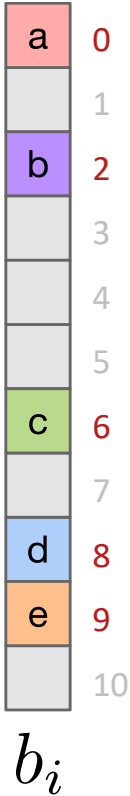
Vector scaling example with repeaters

$$x_i = \underline{b_i} \cdot c$$



Vector scaling example with repeaters

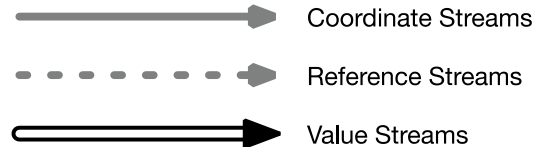
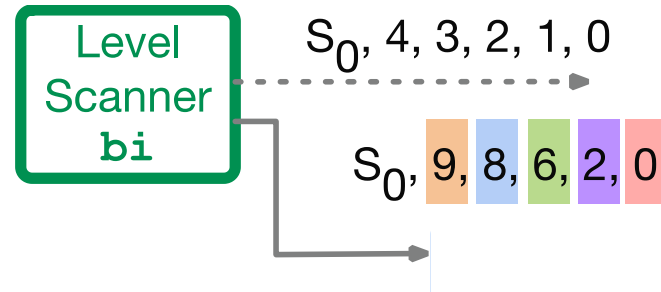
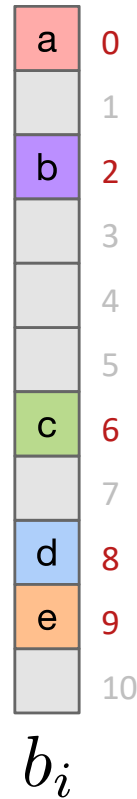
$$x_i = \underline{b_i} \cdot c$$



- Coordinate Streams
- Reference Streams
- Value Streams

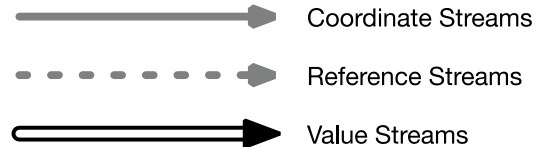
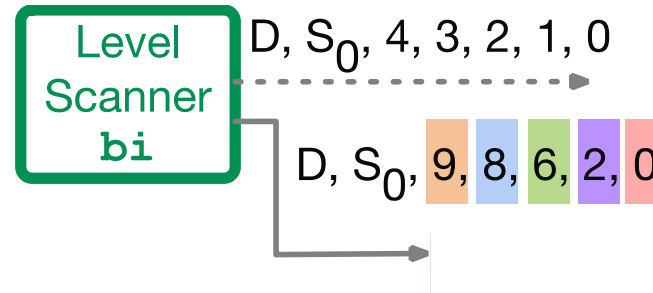
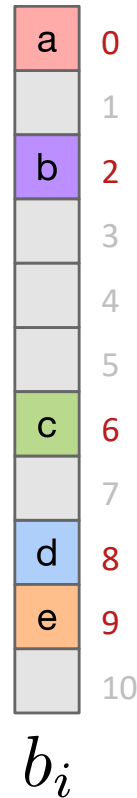
Vector scaling example with repeaters

$$x_i = \underline{b_i} \cdot c$$



Vector scaling example with repeaters

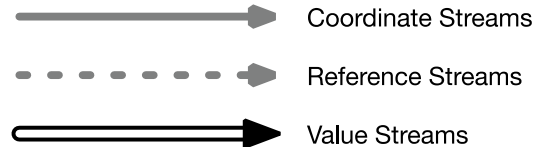
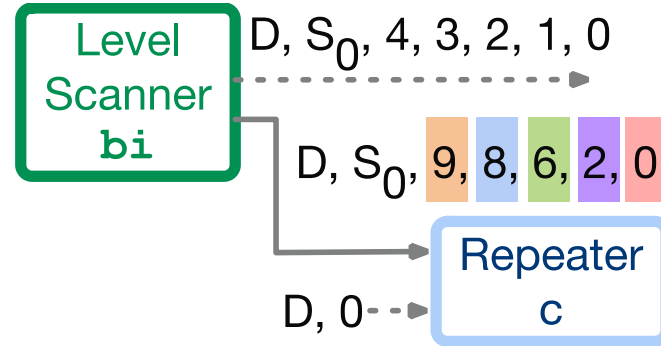
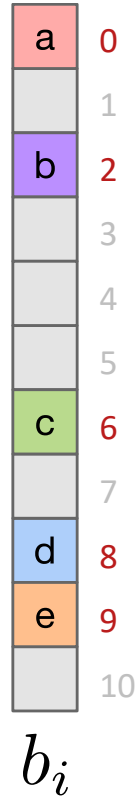
$$x_i = \underline{b_i} \cdot c$$



Vector scaling example with repeaters

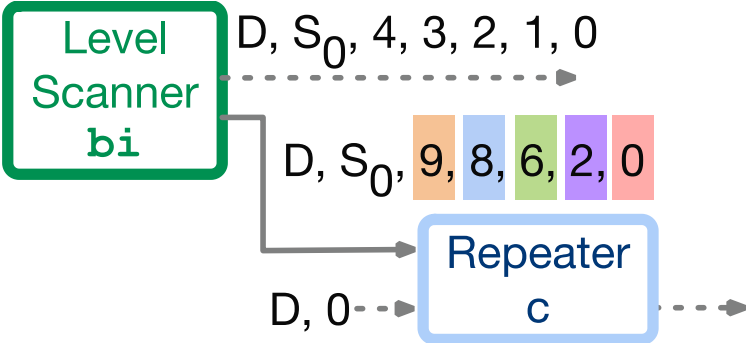
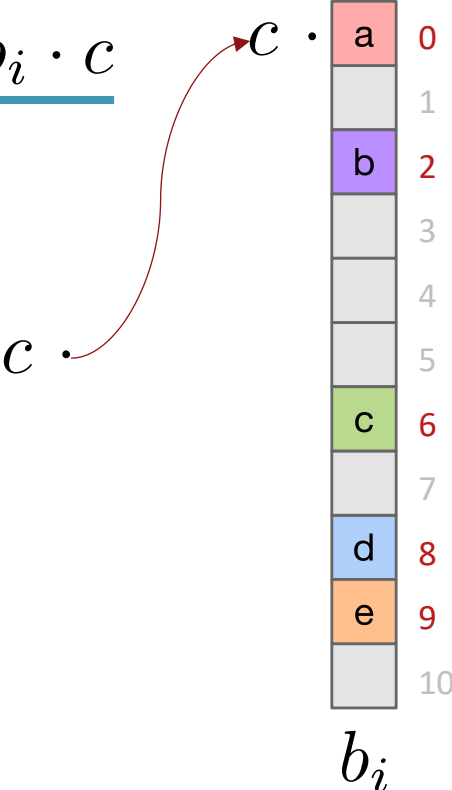
$$x_i = \underline{b_i} \cdot c$$

$c \cdot$



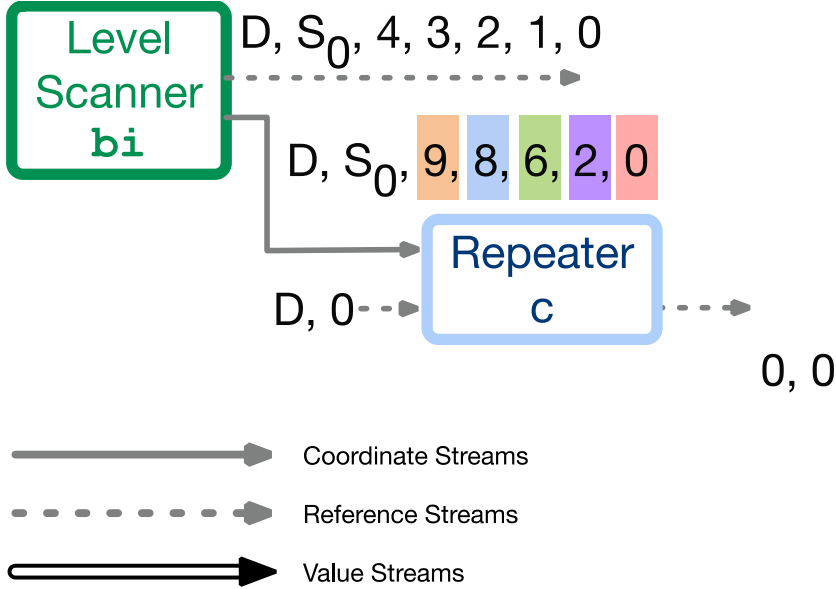
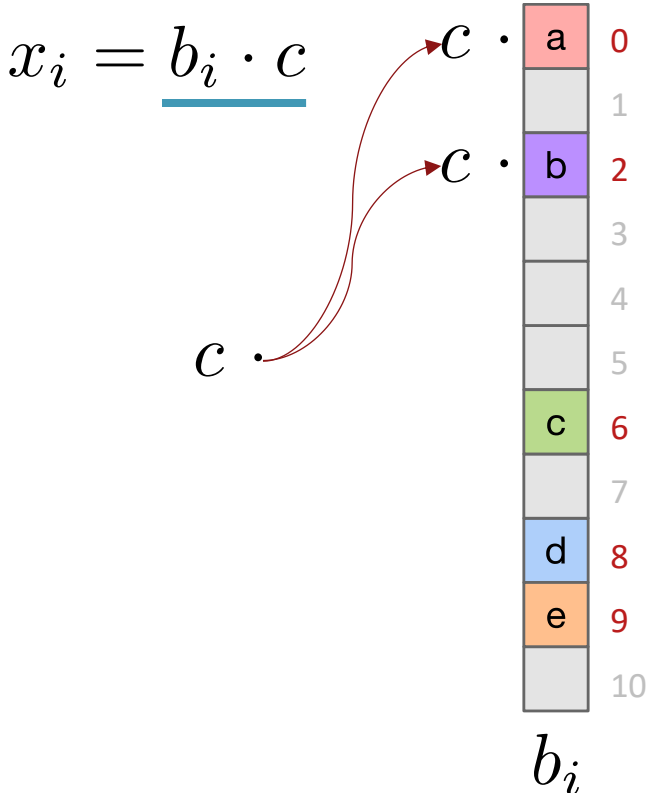
Vector scaling example with repeaters

$$x_i = \underline{b_i} \cdot c$$

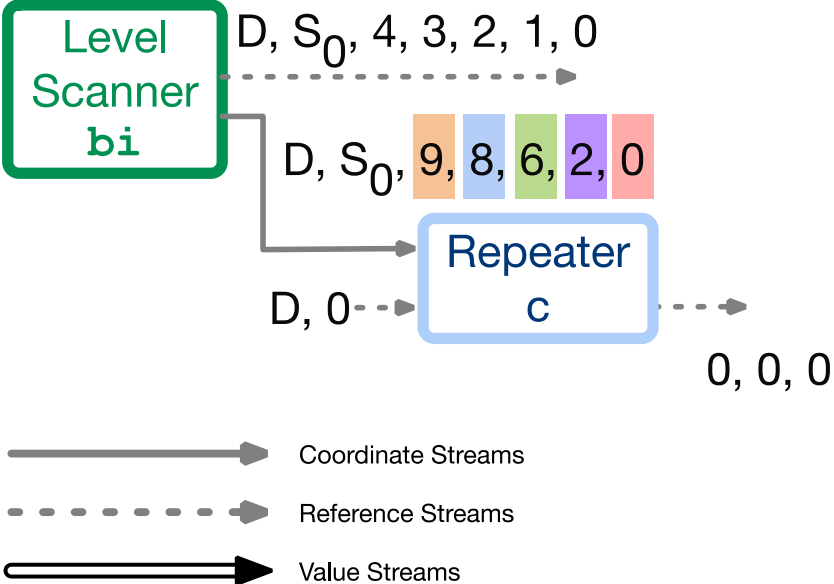
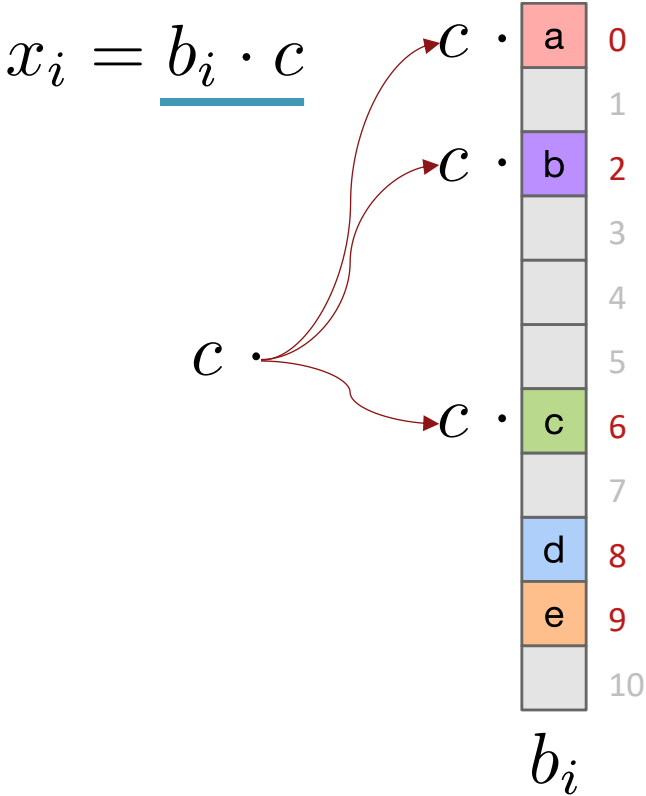


- Coordinate Streams
- Reference Streams
- Value Streams

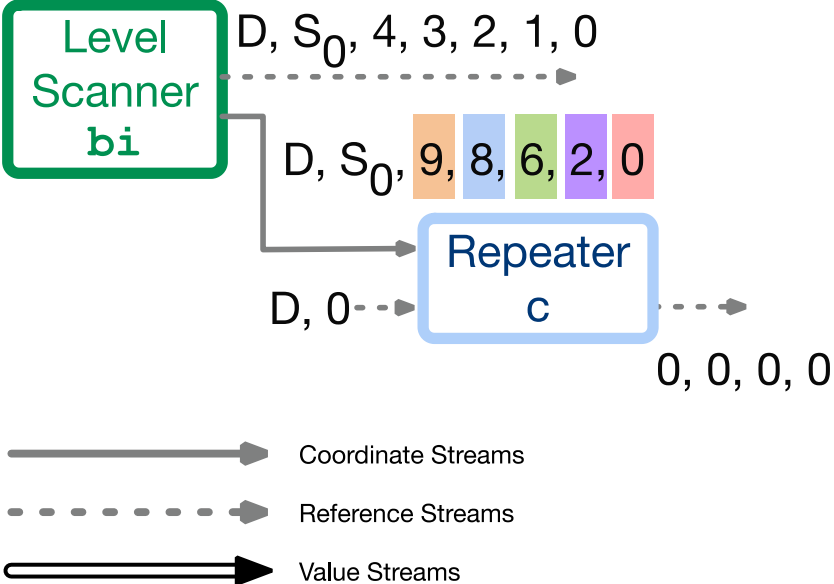
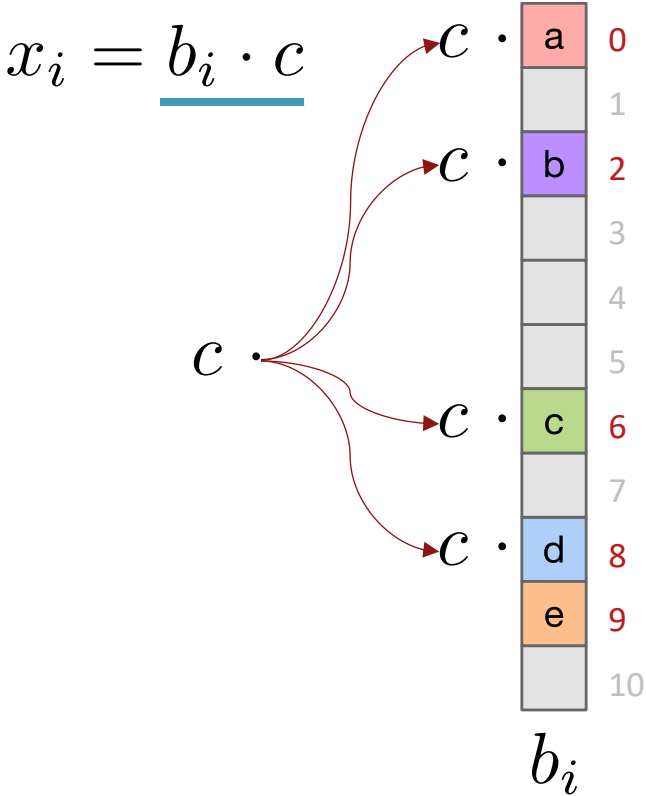
Vector scaling example with repeaters



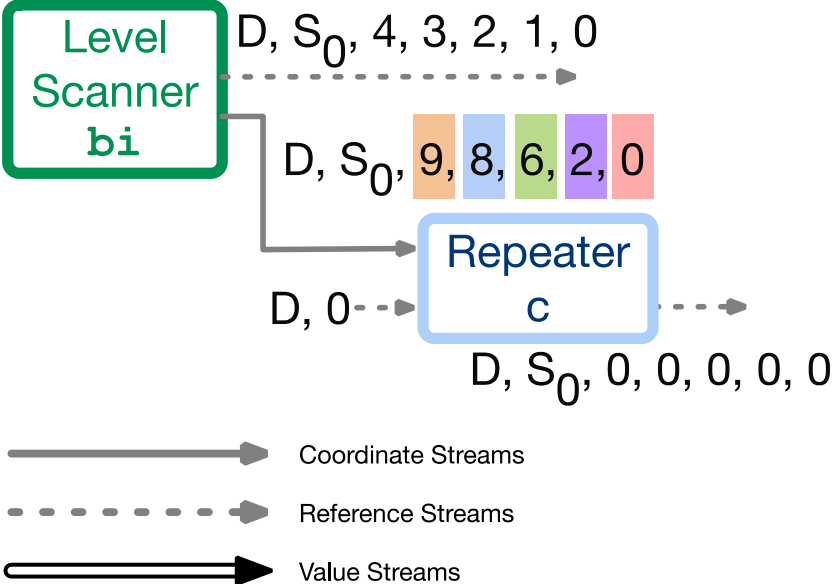
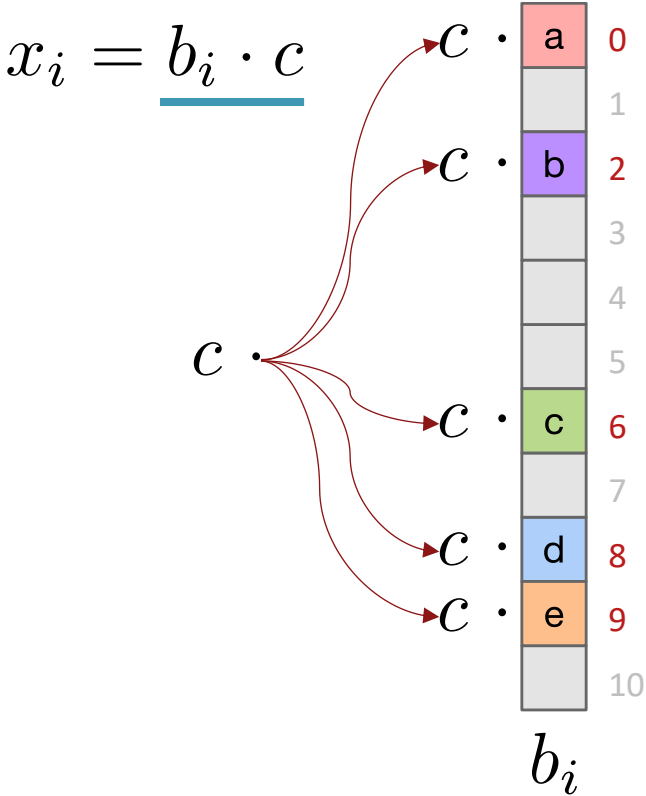
Vector scaling example with repeaters



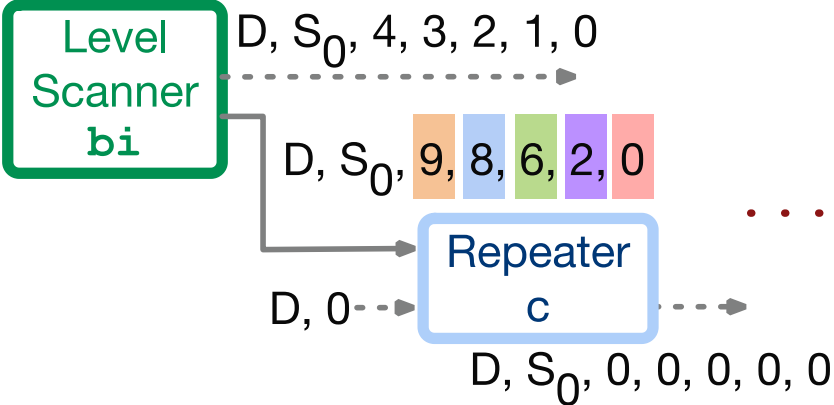
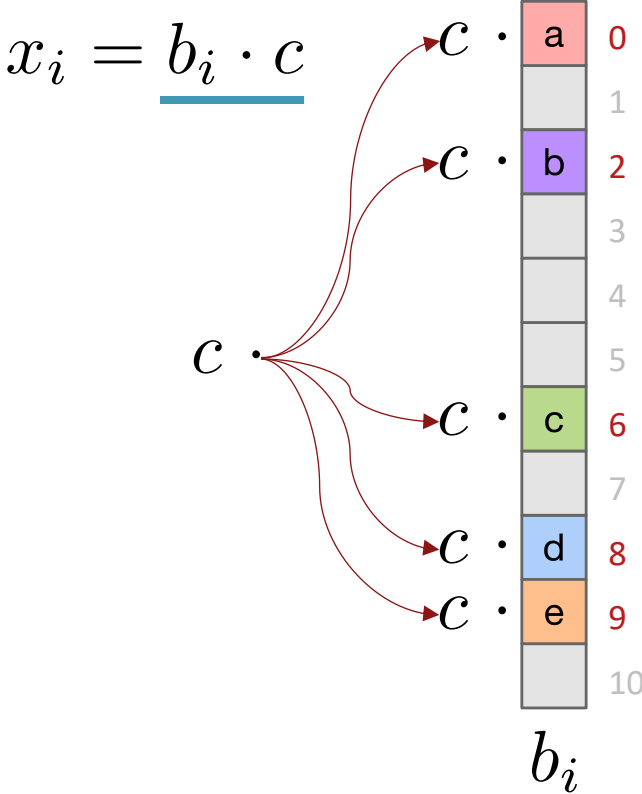
Vector scaling example with repeaters



Vector scaling example with repeaters

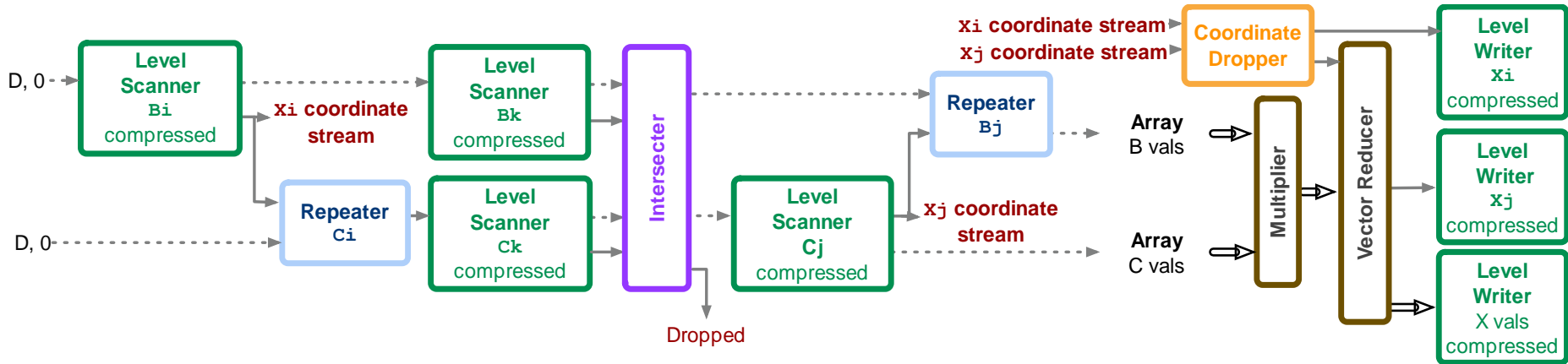


Vector scaling example with repeaters

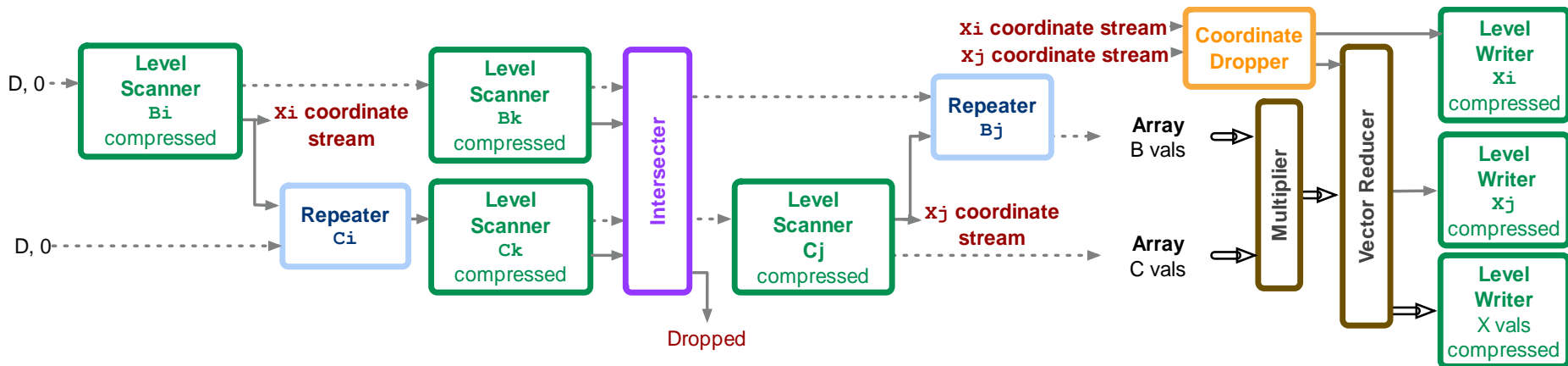


- Coordinate Streams
- Reference Streams
- Value Streams

Primitives compose to compute expressions: $S_pM * S_pM$

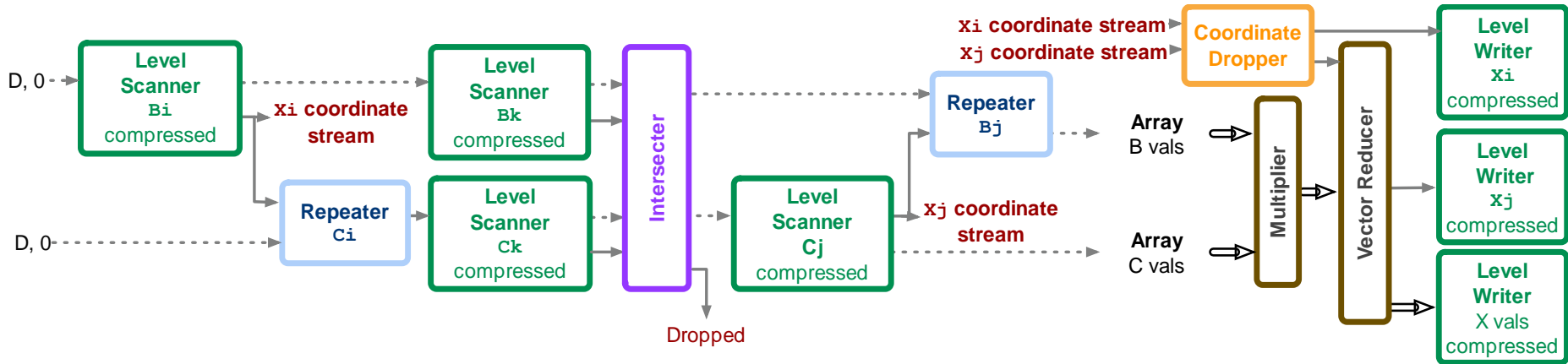


Primitives compose to compute expressions: SpM*SpM



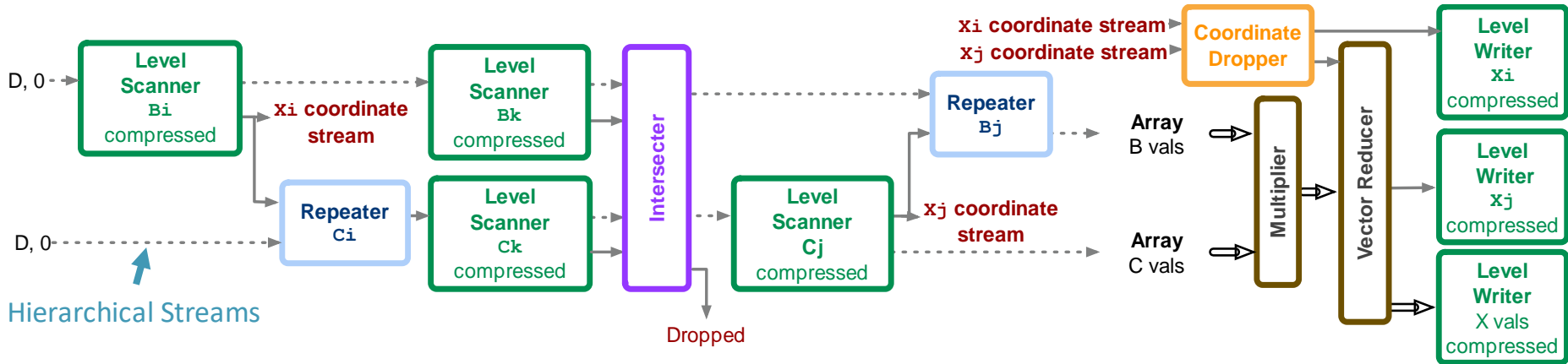
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



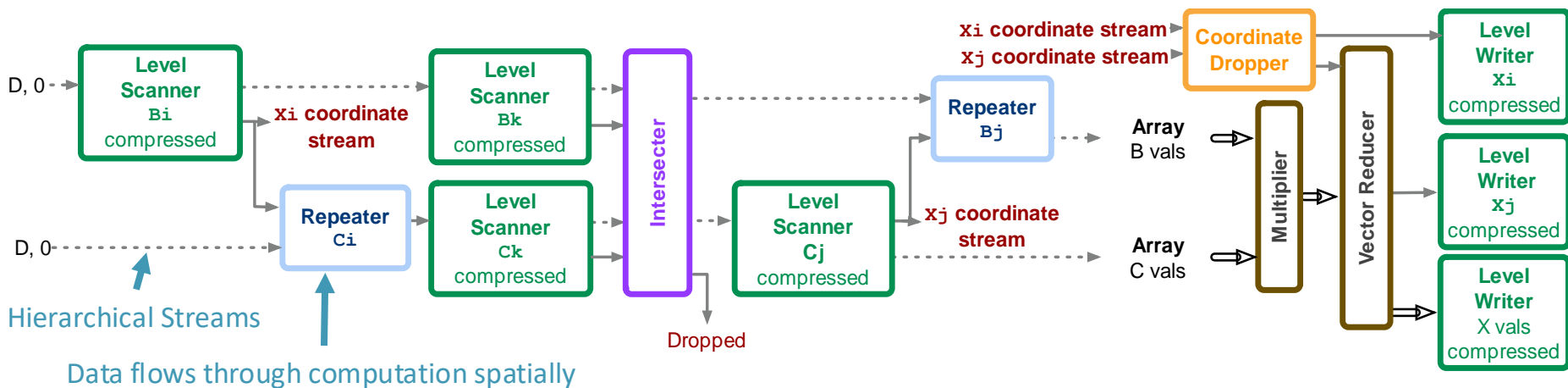
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



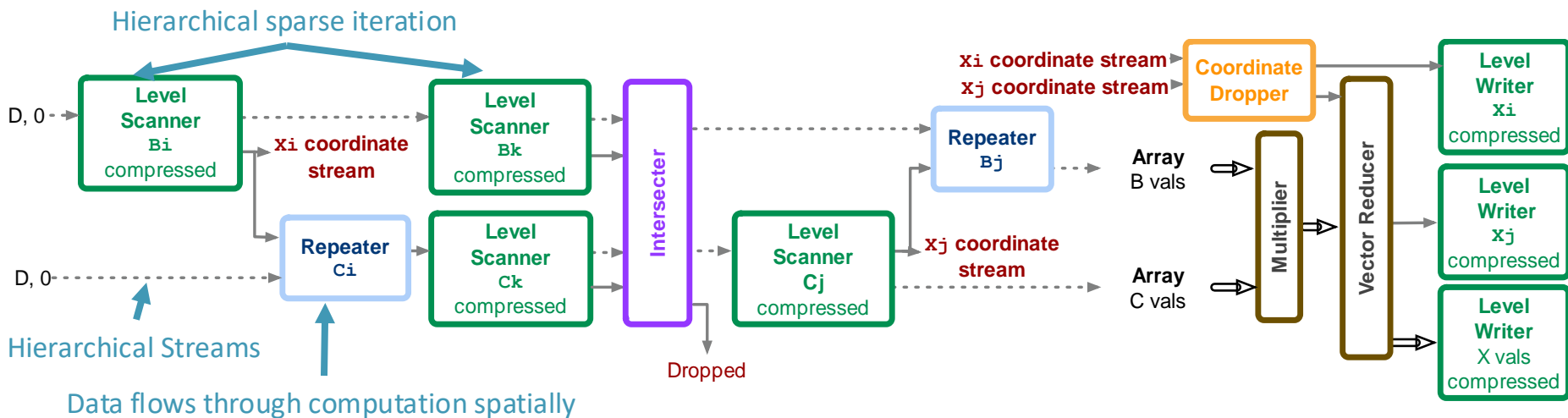
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: $SpM * SpM$



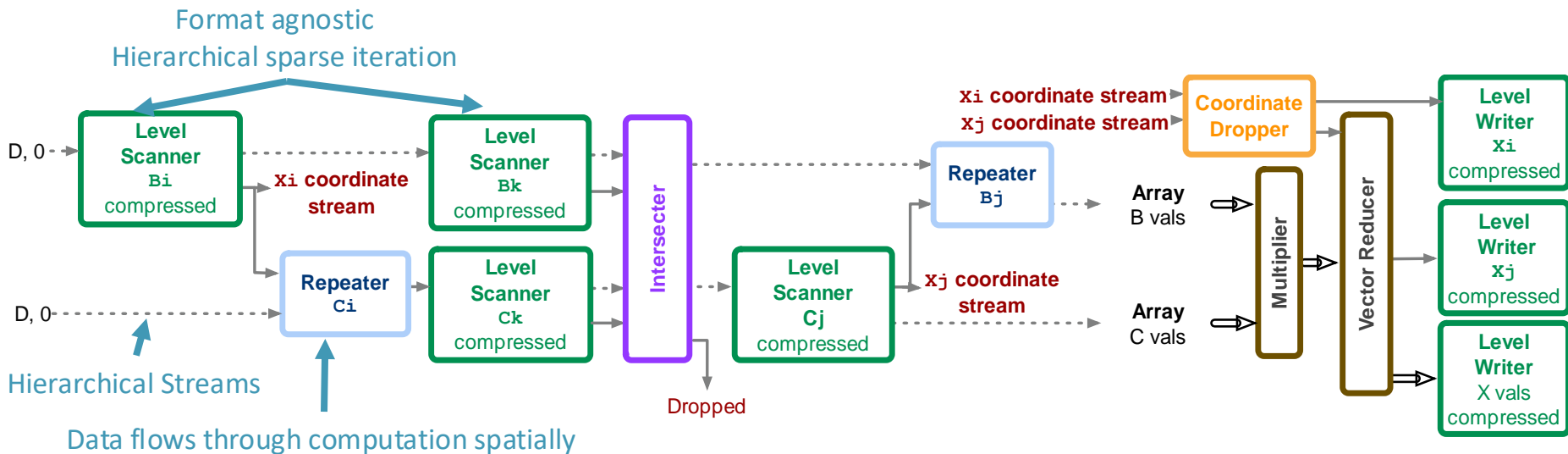
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



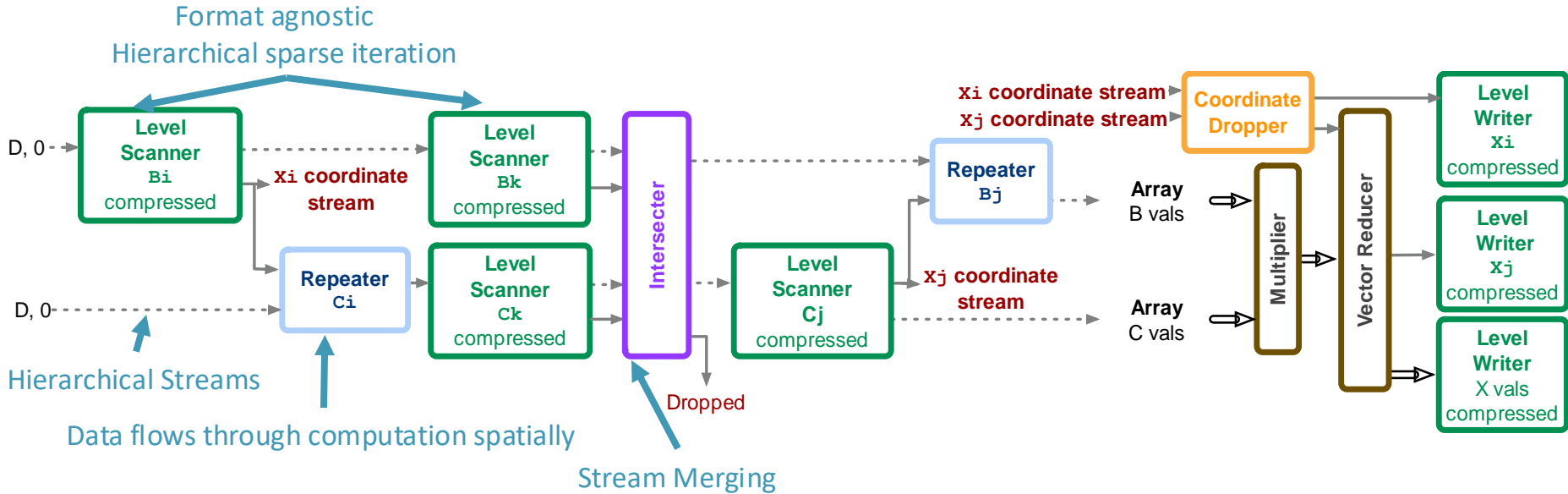
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



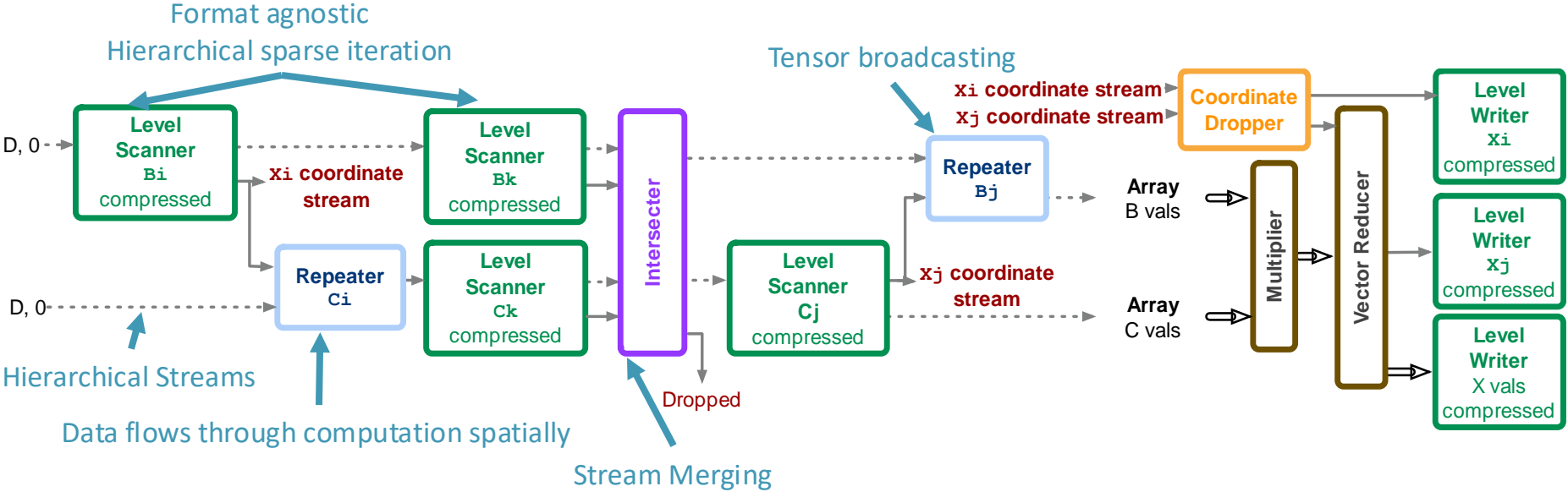
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



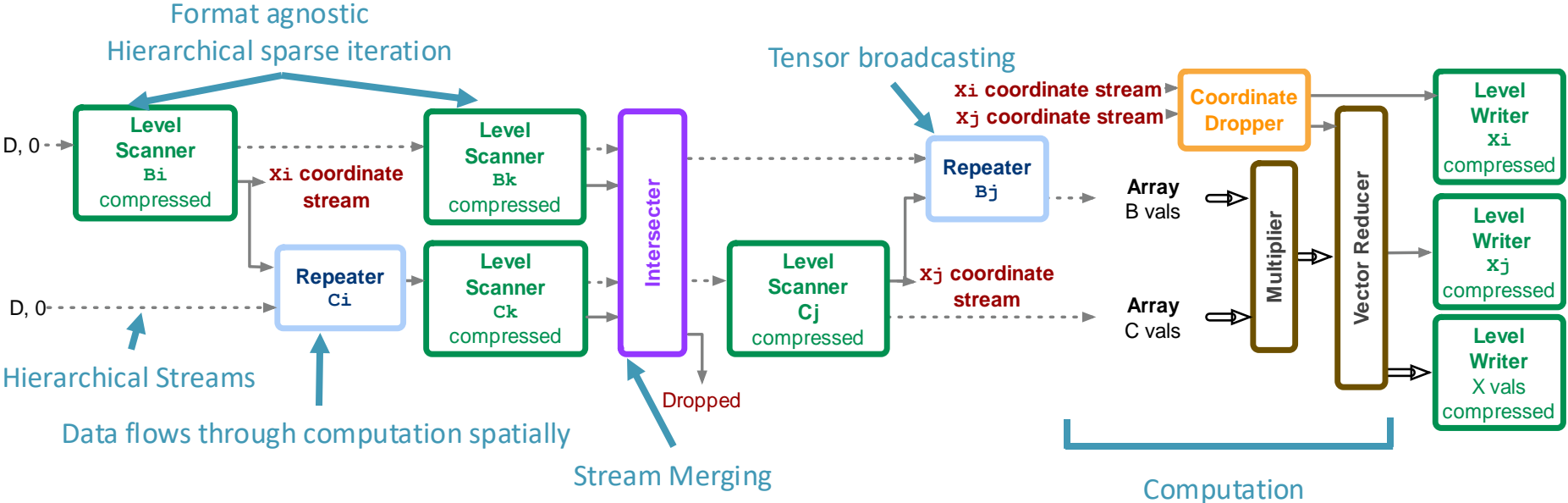
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



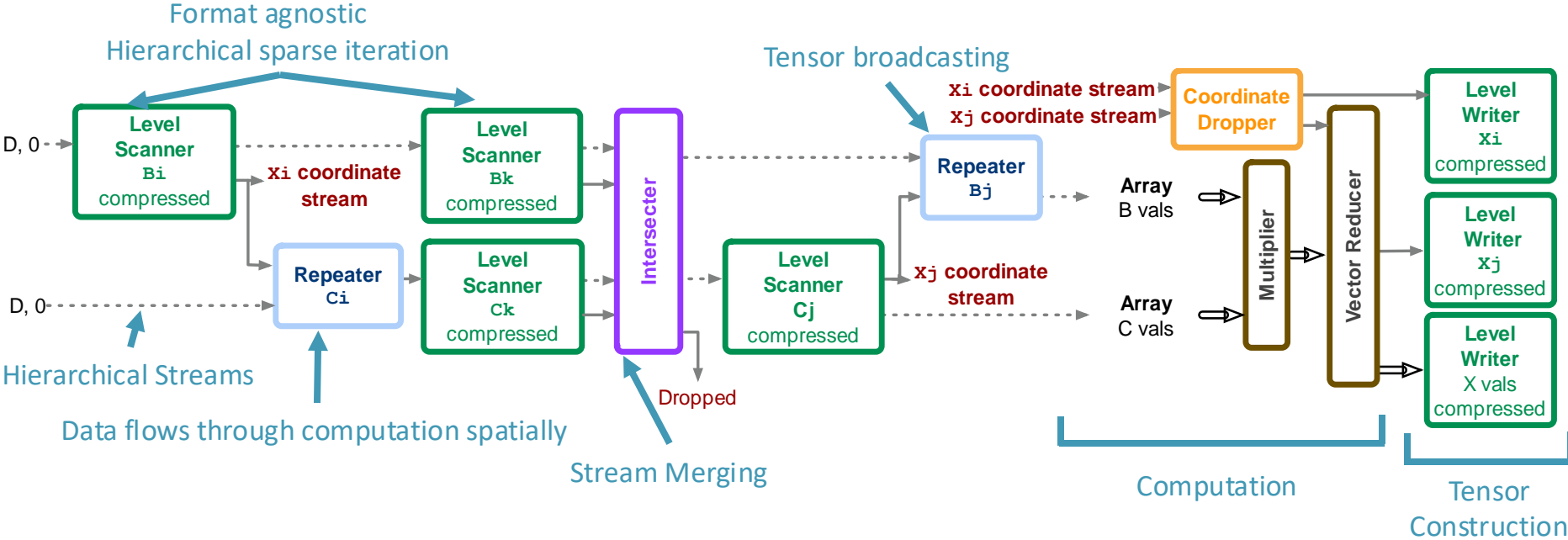
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



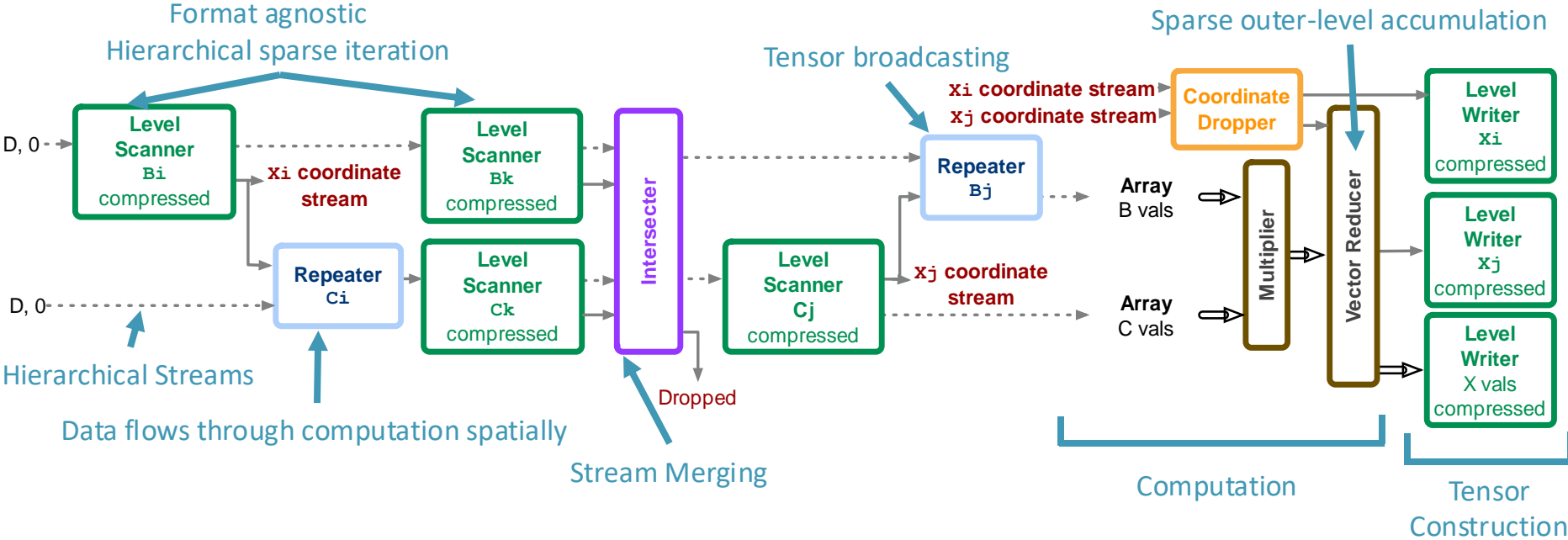
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



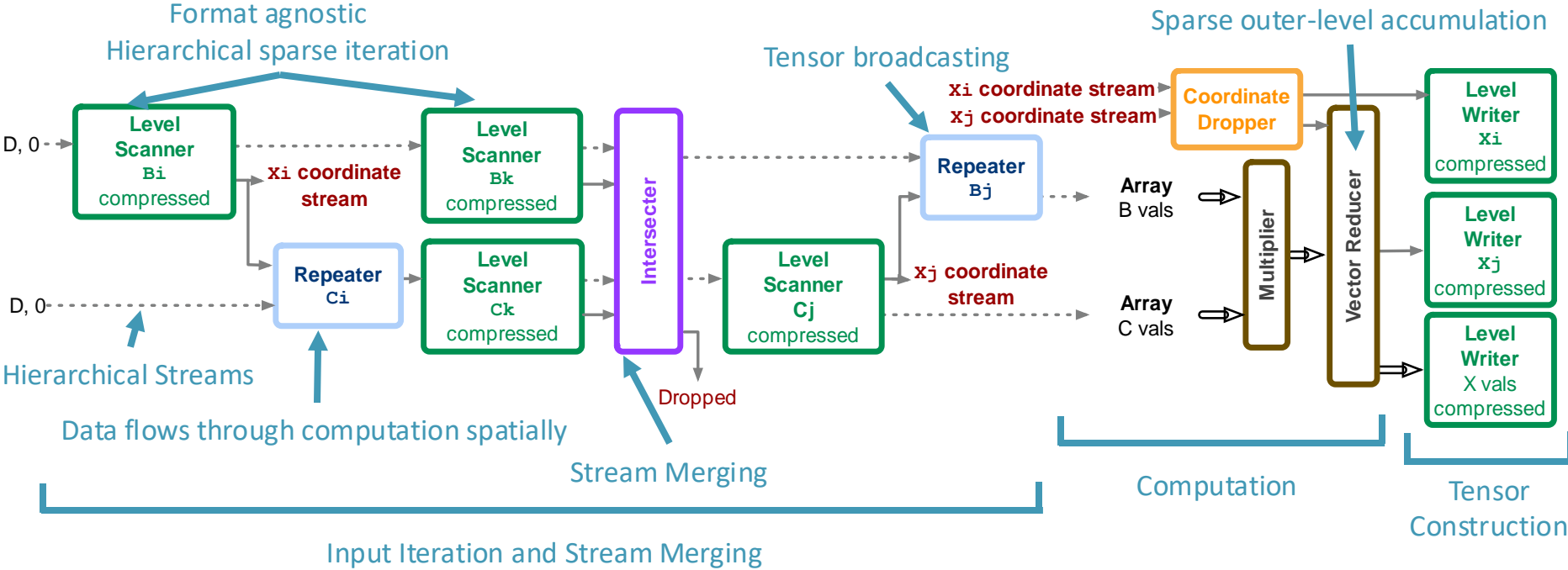
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



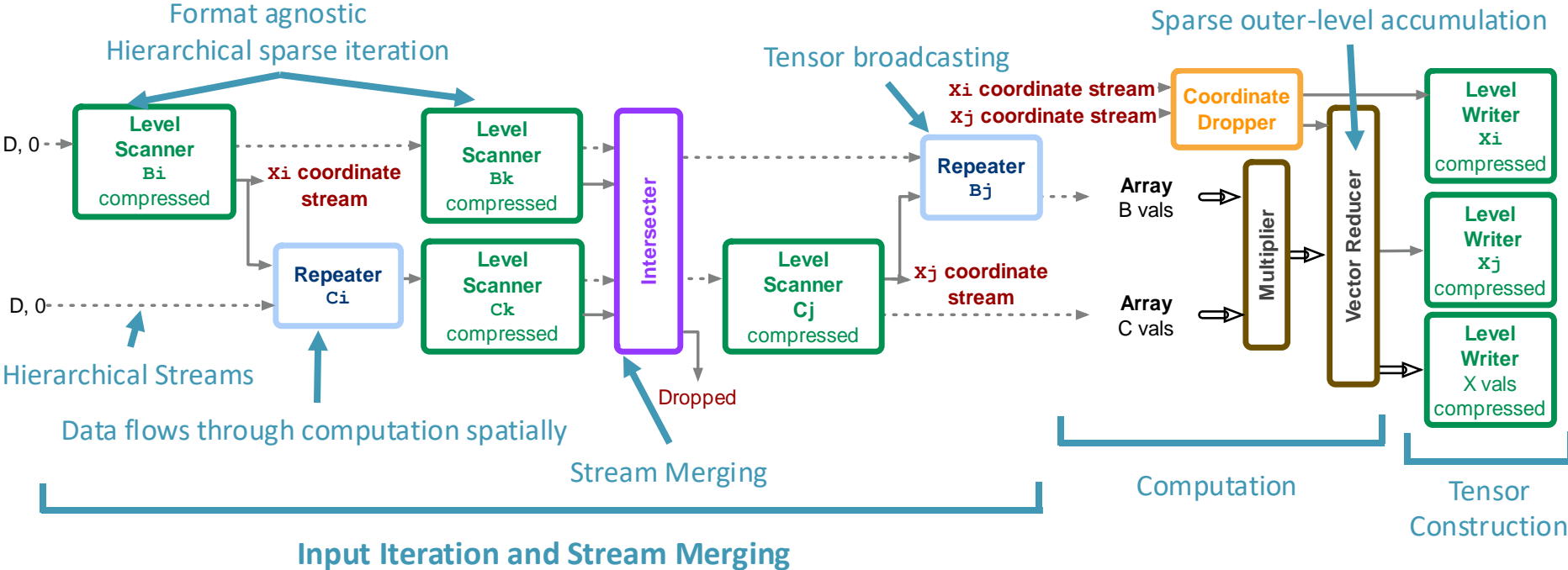
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



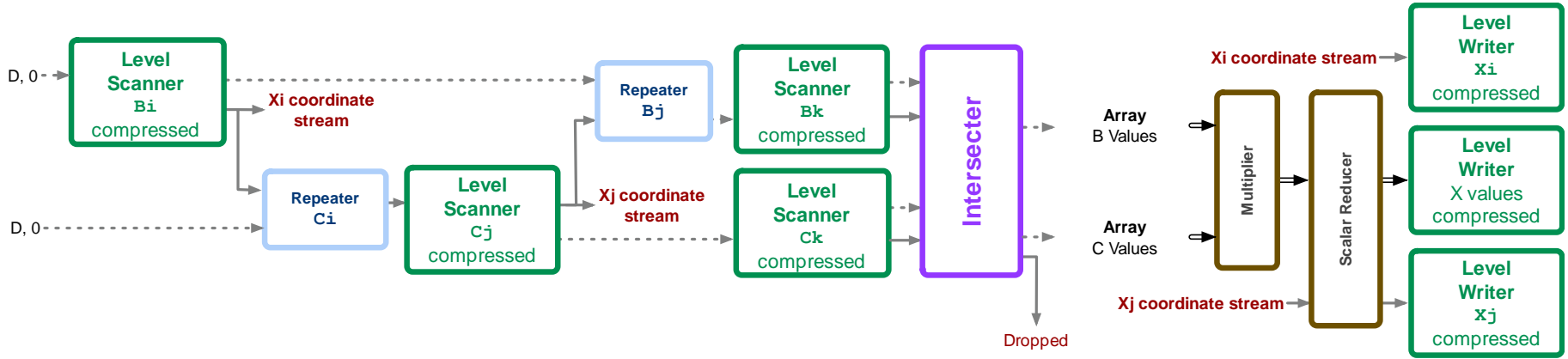
$$\forall_i \forall_k \forall_j X_{ij} = B_{ik} \cdot C_{kj}$$

Primitives compose to compute expressions: SpM*SpM



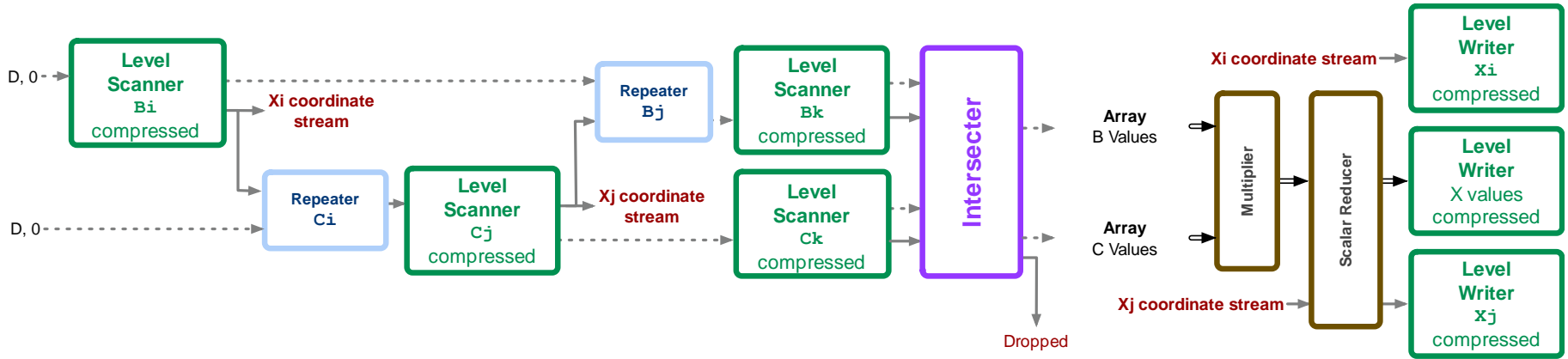
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Inner-product algorithm in SAM



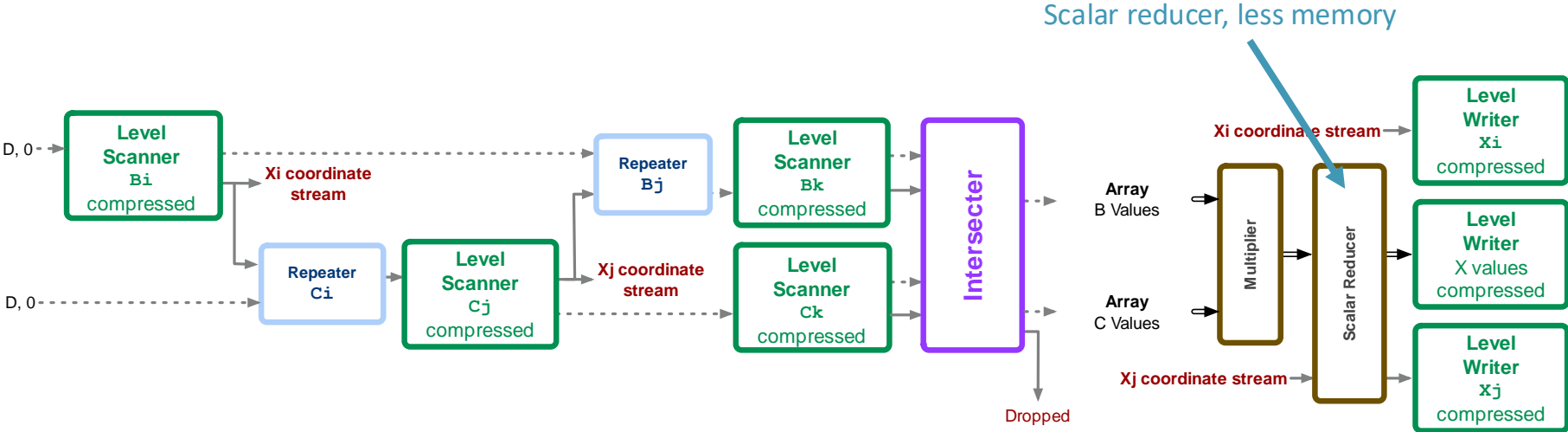
$$\forall_i \forall_j \forall_k X_{ij} = B_{ik} * C_{kj}$$

Inner-product algorithm in SAM



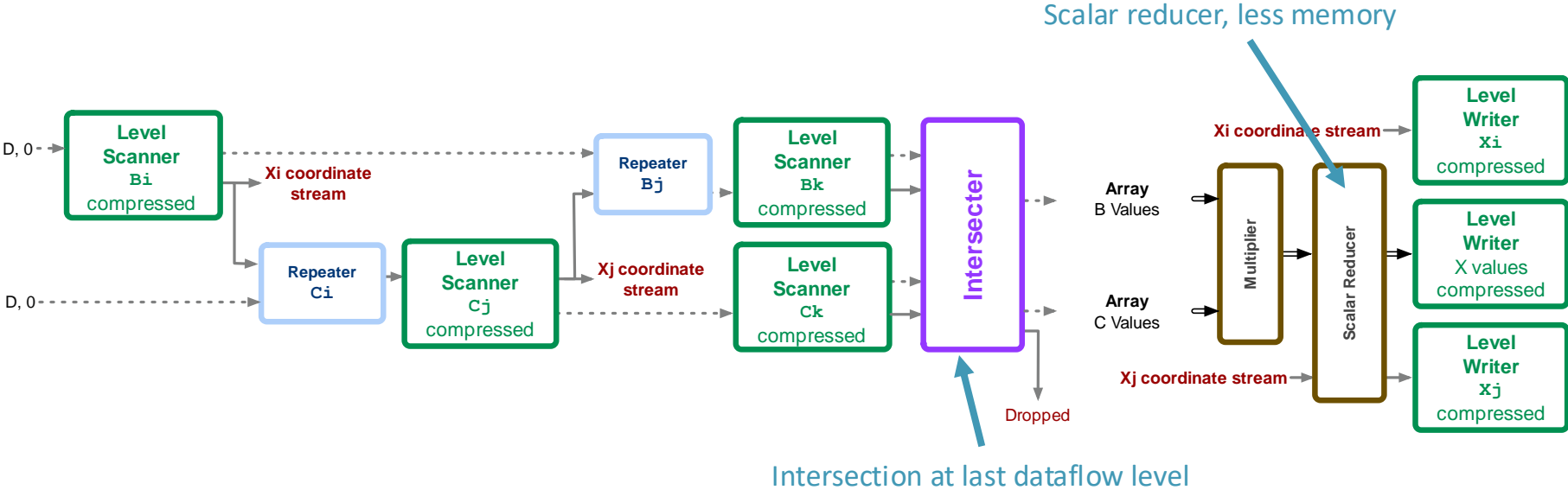
$$\forall_i \forall_j \forall_k X_{ij} = B_{ik} * C_{kj}$$

Inner-product algorithm in SAM



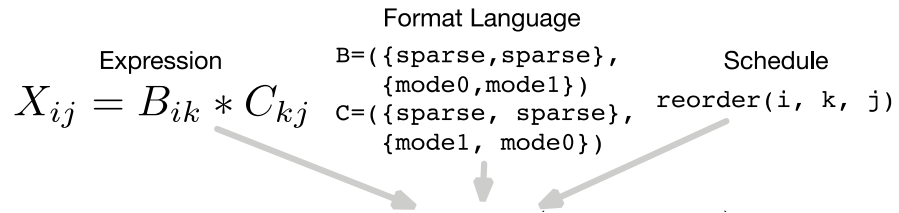
$$\forall_i \forall_j \forall_k X_{ij} = B_{ik} * C_{kj}$$

Inner-product algorithm in SAM

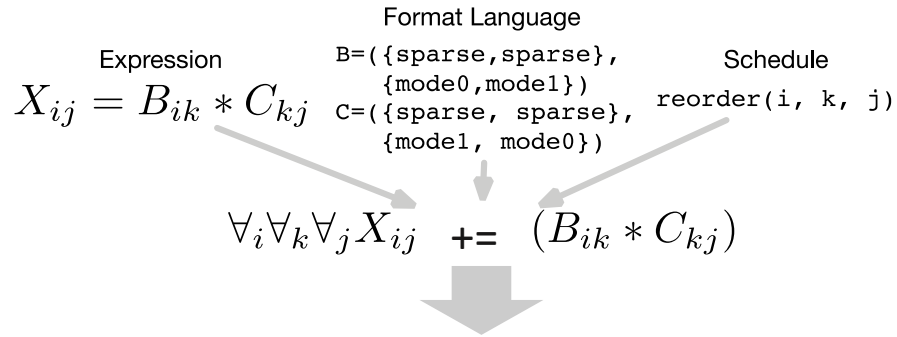


$$\forall_i \forall_j \forall_k X_{ij} = B_{ik} * C_{kj}$$

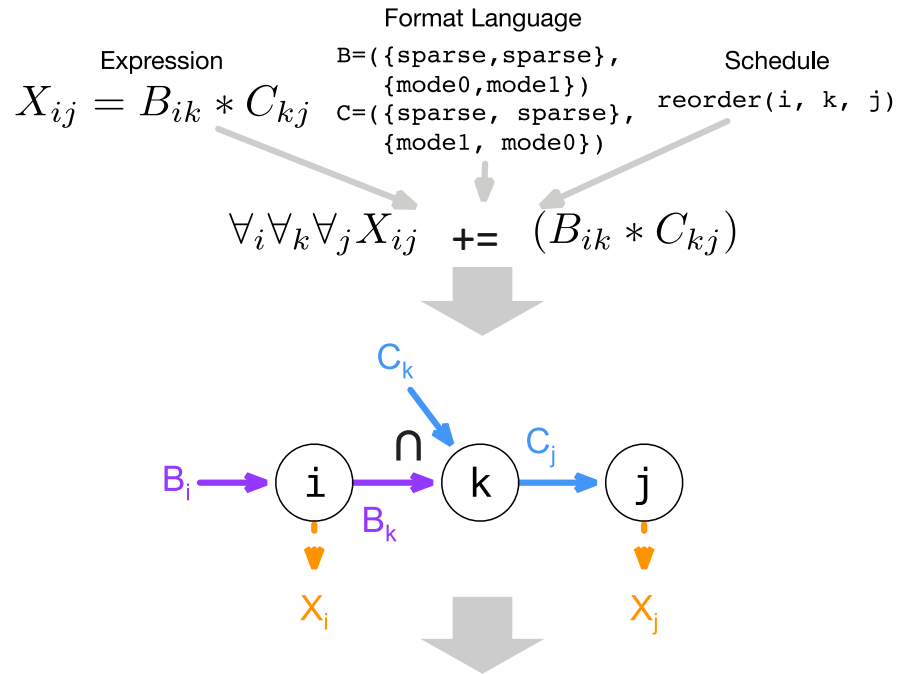
Custard's compiler algorithm to SAM



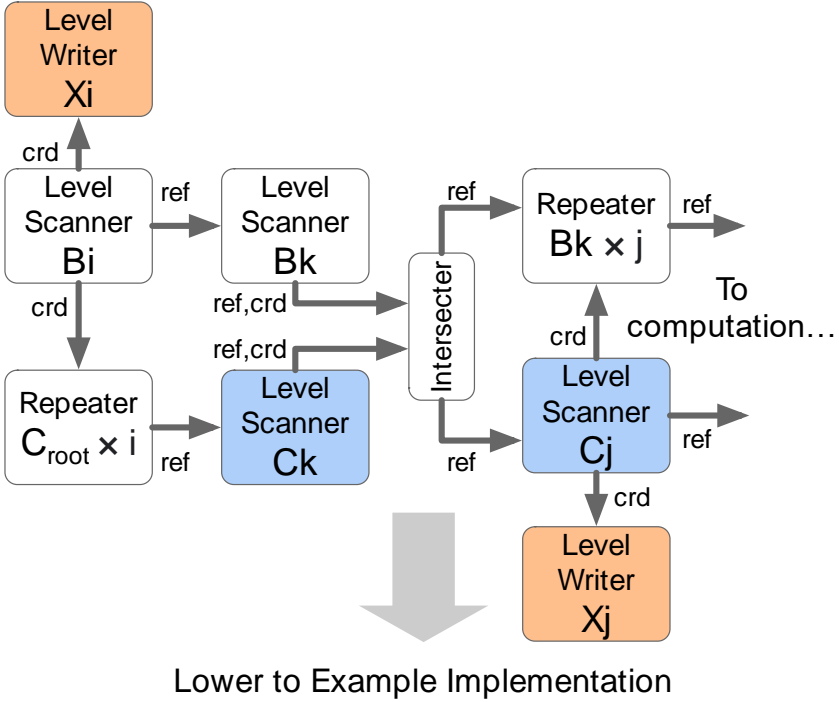
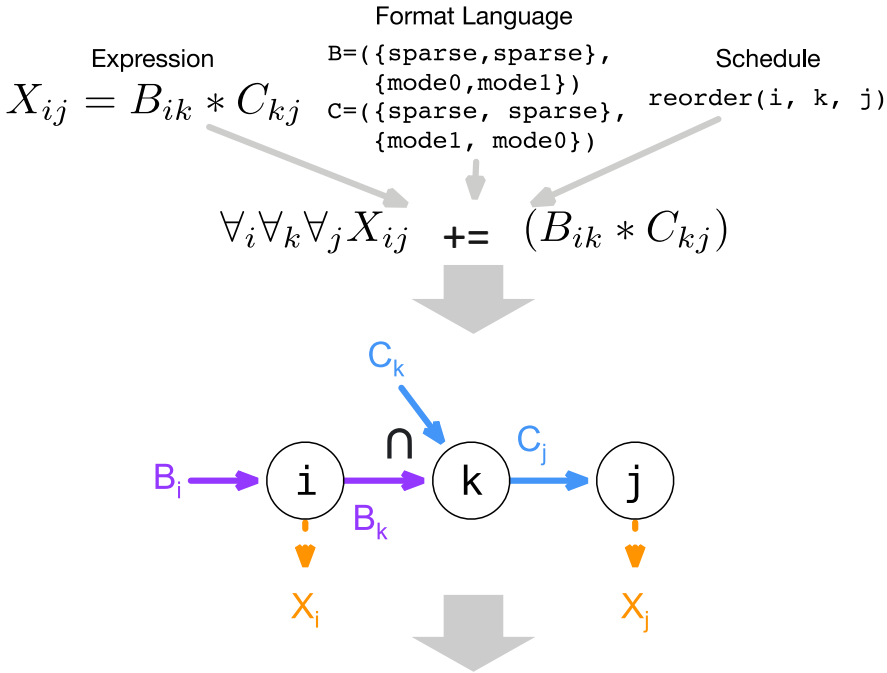
Custard's compiler algorithm to SAM



Custard's compiler algorithm to SAM



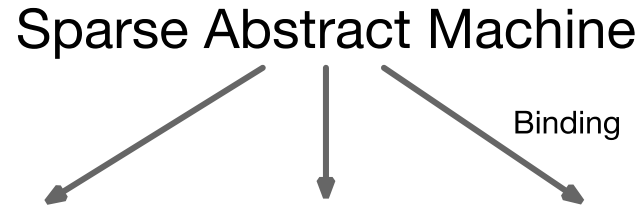
Custard's compiler algorithm to SAM



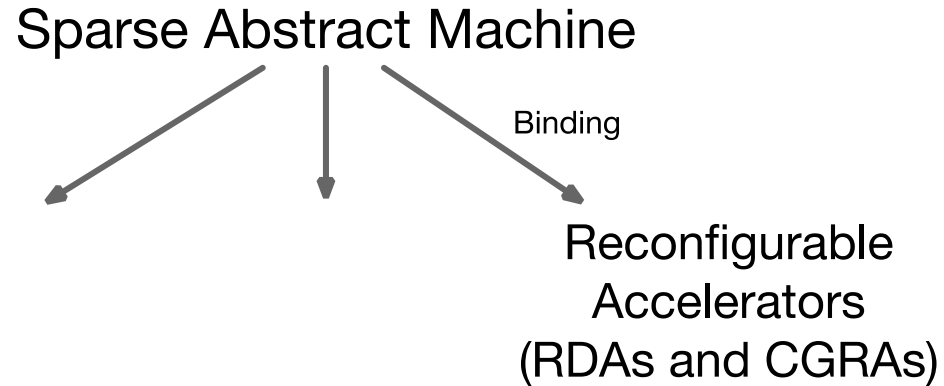
Demo: Generating SAM graphs with Custard

- > `./sparse_demo.sh compile`
 - This runs the applications in `./sam/compiler/sam-kernels.sh` through the Custard compiler
 - All SAM graphs generated in `./sam/compiler/sam-outputs/`
- View the SpMSpM kernel `matmul_ijk` in `./sam/compiler/sam-outputs/png/matmul_ijk.png` in VSCode or using `docker cp`
- We will also view a smaller kernel, `mat_elemadd` in `./sam/compiler/sam-outputs/png/mat_elemadd.png`, which we will be using for the rest of the demo

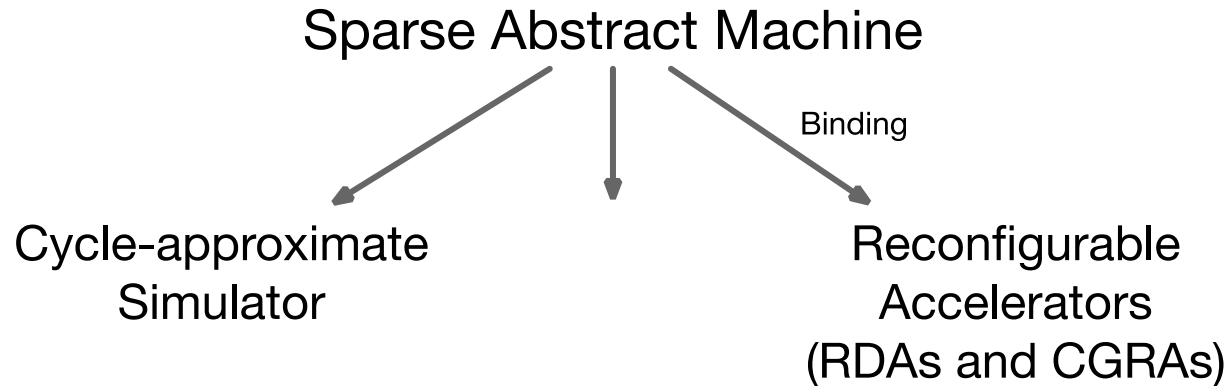
Although abstract, SAM binds to real hardware



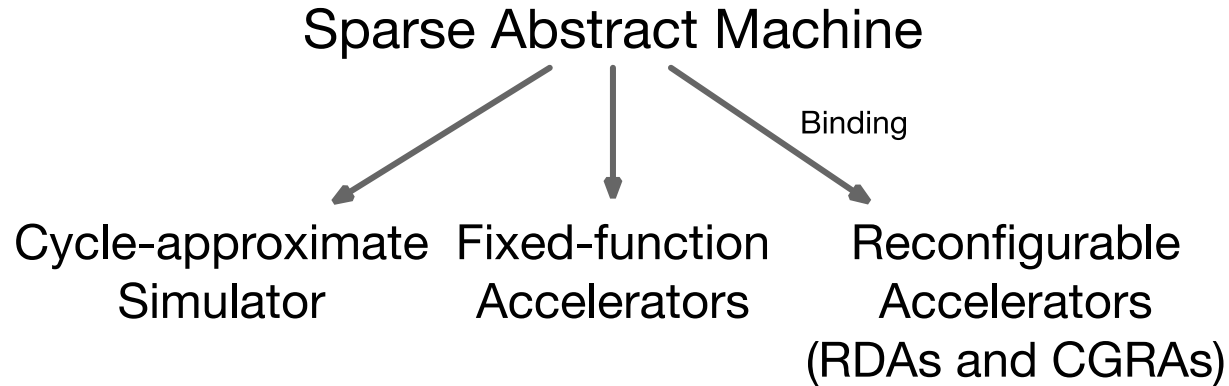
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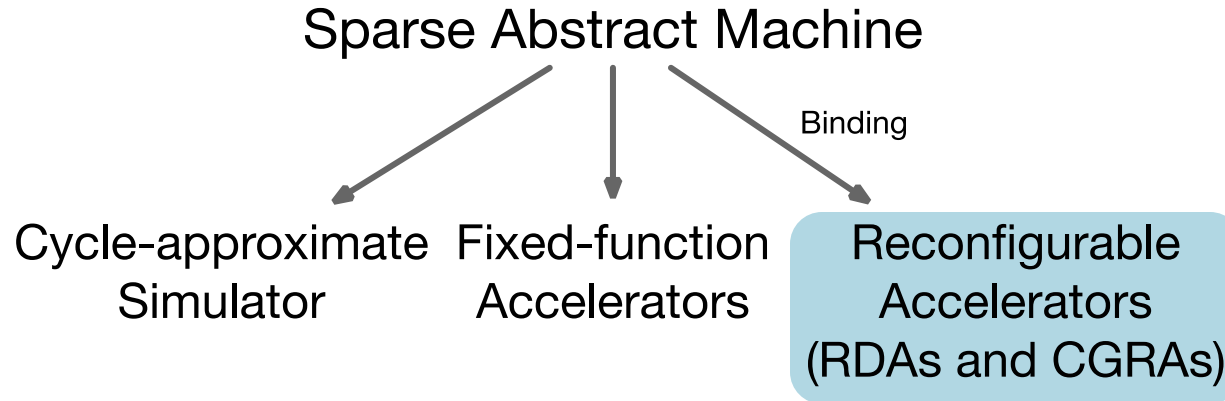
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Although abstract, SAM binds to real hardware



Programming dataflow requires an abstract machine that a compiler can target

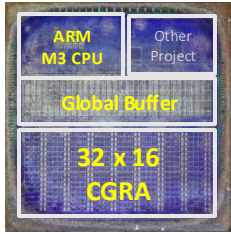
High-Level
Input Languages
(APIs)



Sparse Accelerator

Programming dataflow requires an abstract machine that a compiler can target

High-Level
Input Languages
(APIs)



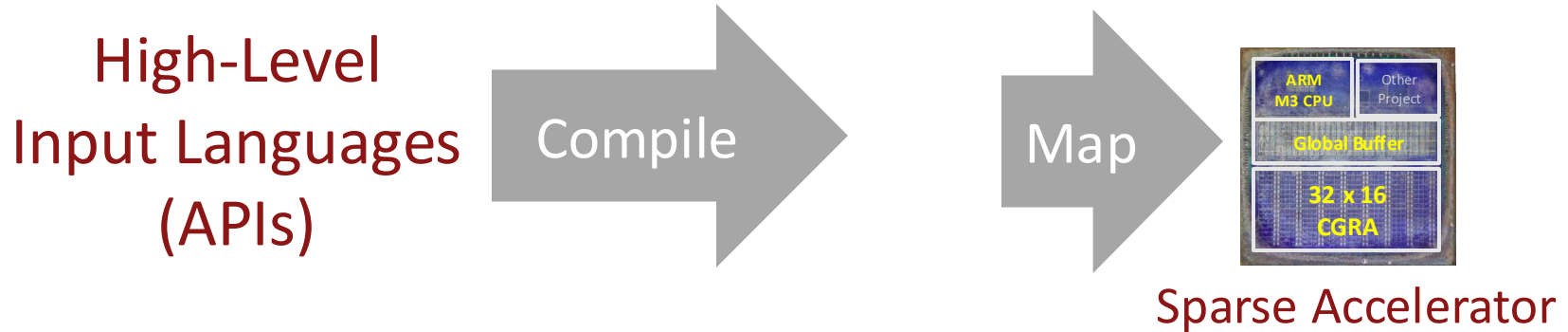
Sparse Accelerator

Programming dataflow requires an abstract machine that a compiler can target



A clean interface decouples the compiler from specific hardware implementations

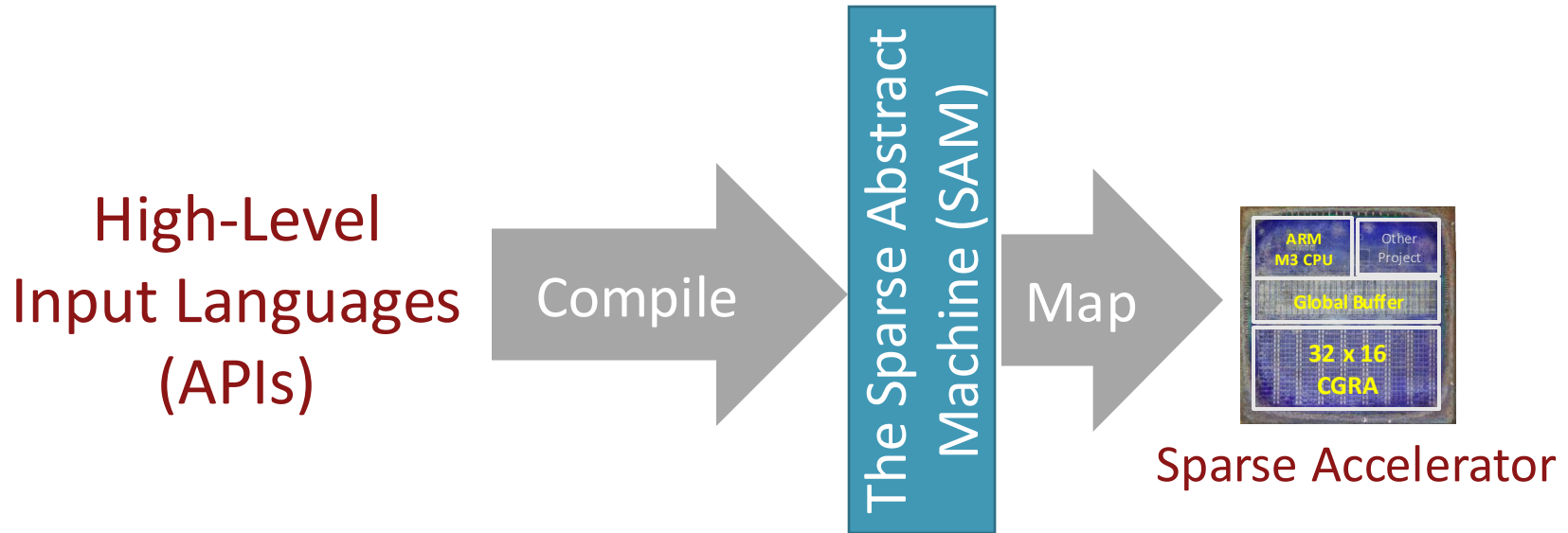
Programming dataflow requires an abstract machine that a compiler can target



A clean interface decouples the compiler from specific hardware implementations

Programming dataflow requires an abstract machine that a compiler can target

[Hsu et al. ASPLOS 2023]

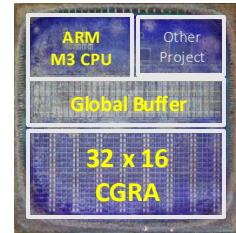
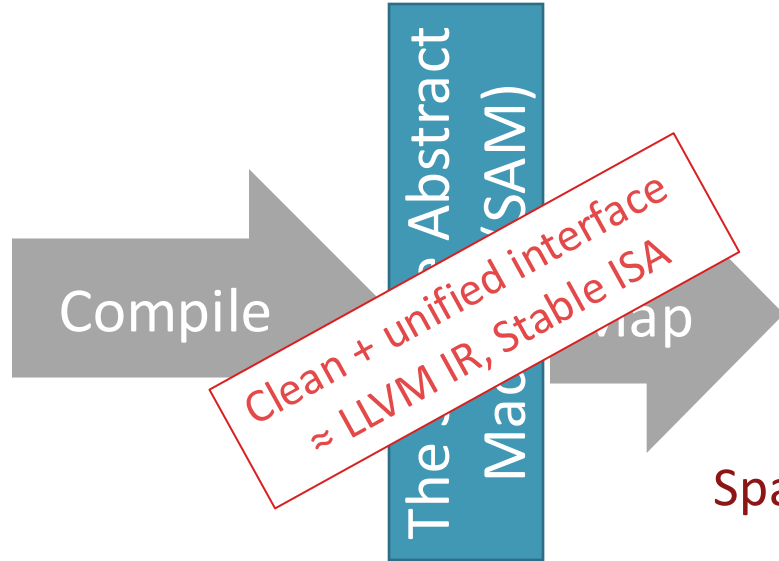


A clean interface decouples the compiler from specific hardware implementations

Programming dataflow requires an abstract machine that a compiler can target

[Hsu et al. ASPLOS 2023]

High-Level
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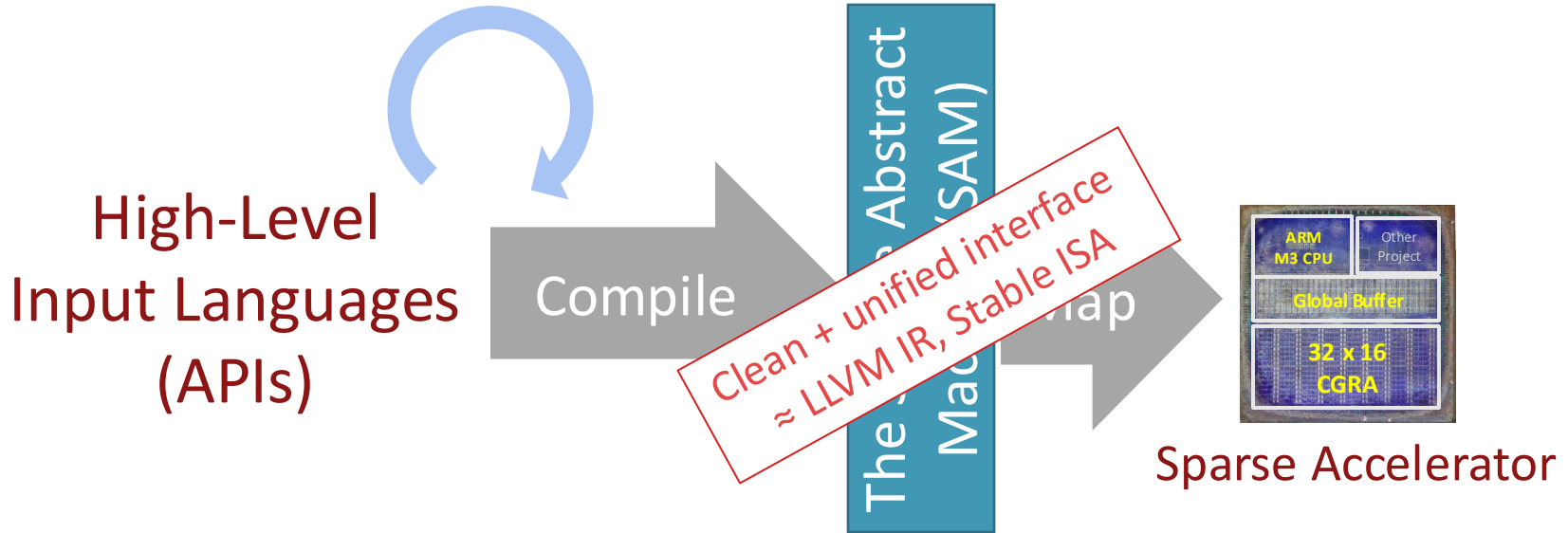


Sparse Accelerator

A clean interface decouples the compiler from specific hardware implementations

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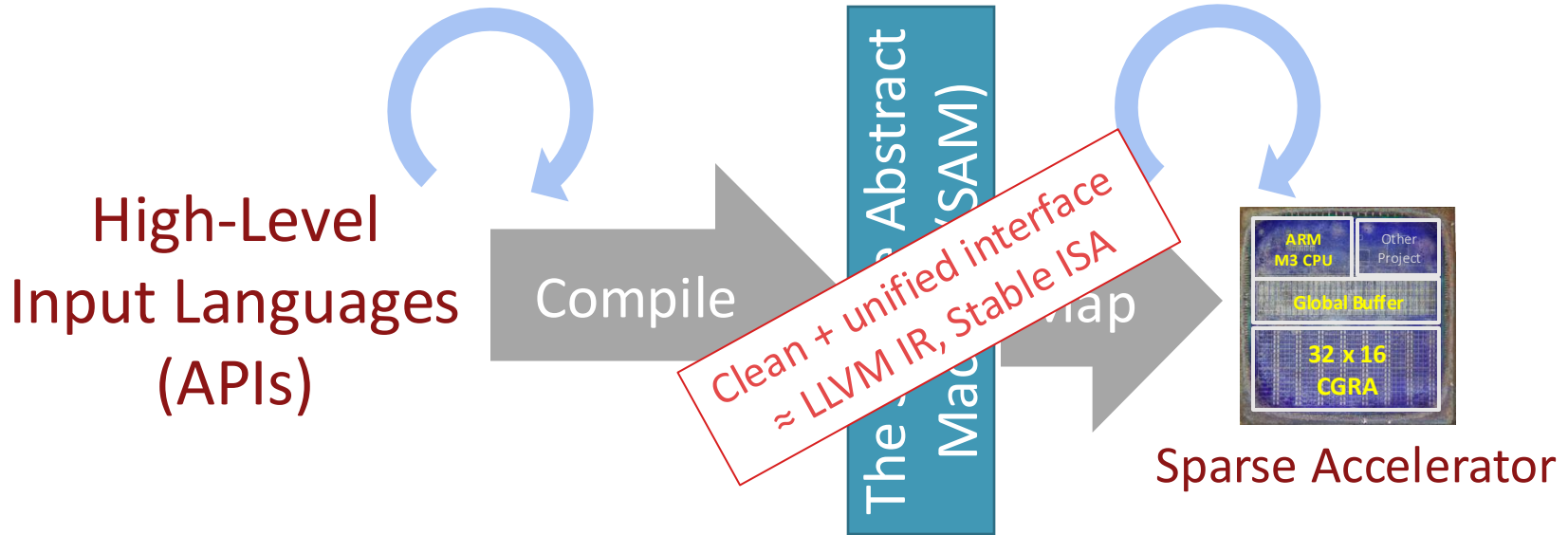
[Hsu et al. ASPLOS 2023]



A clean interface decouples the compiler from specific hardware implementations

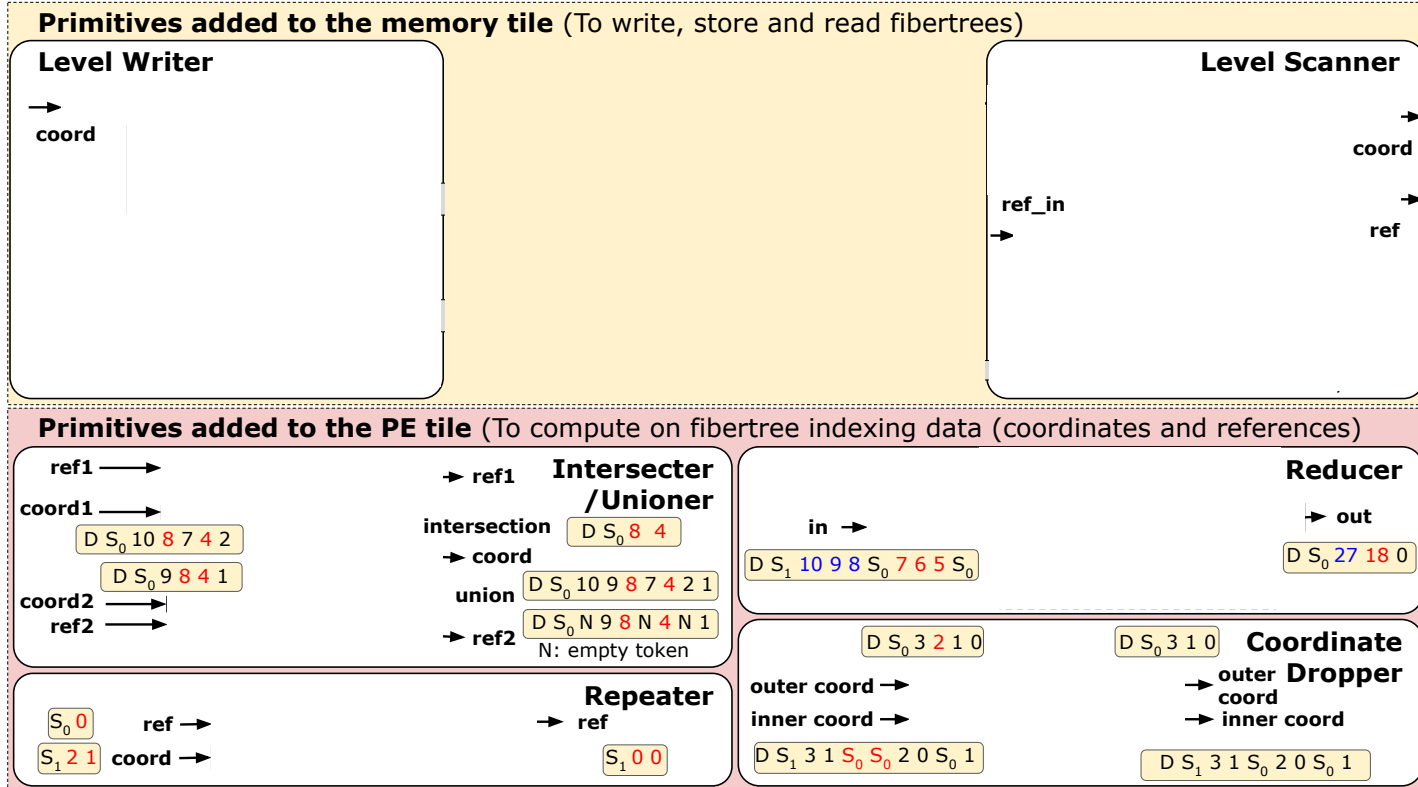
Programming dataflow requires an abstract machine that a compiler can target

[Hsu et al. ASPLOS 2023]

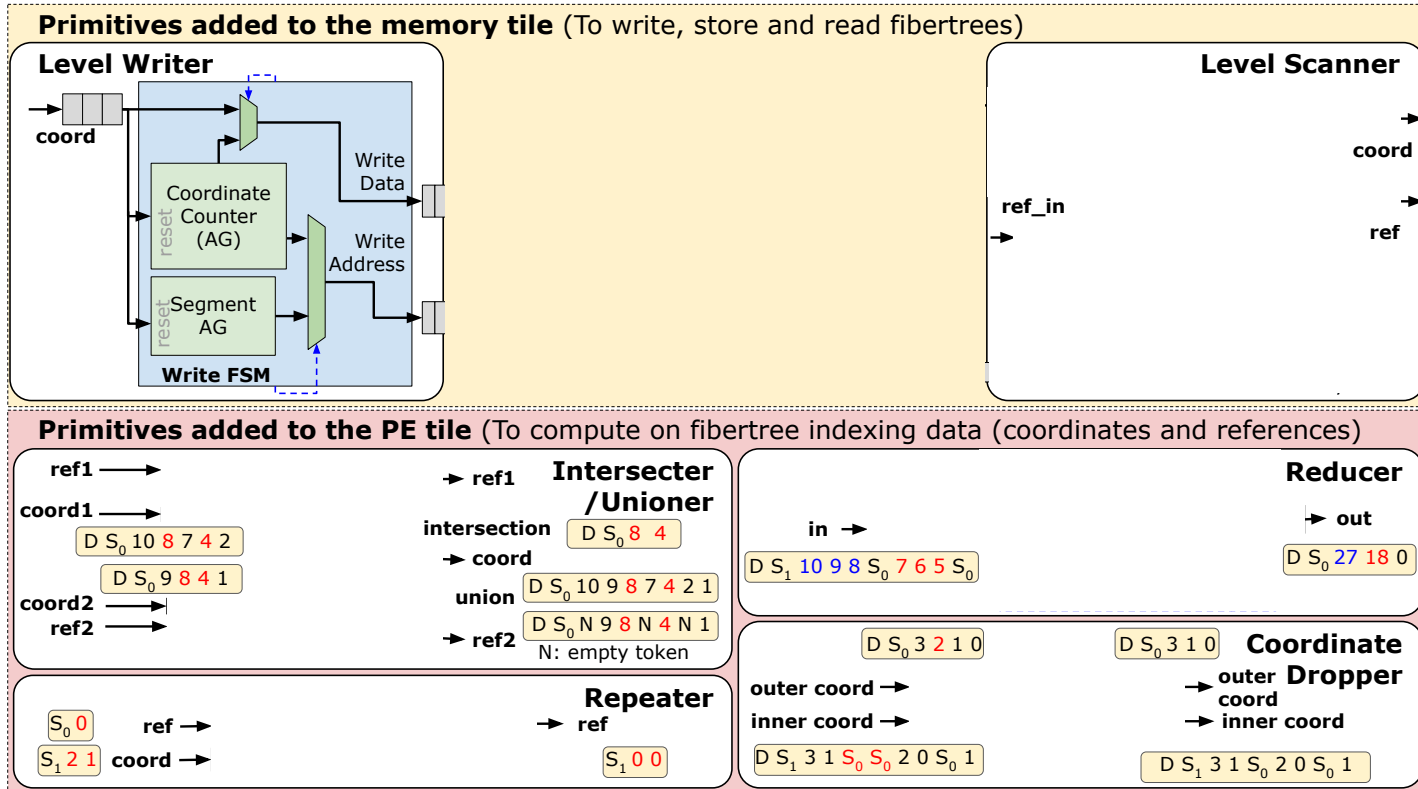


A clean interface decouples the compiler from specific hardware implementations

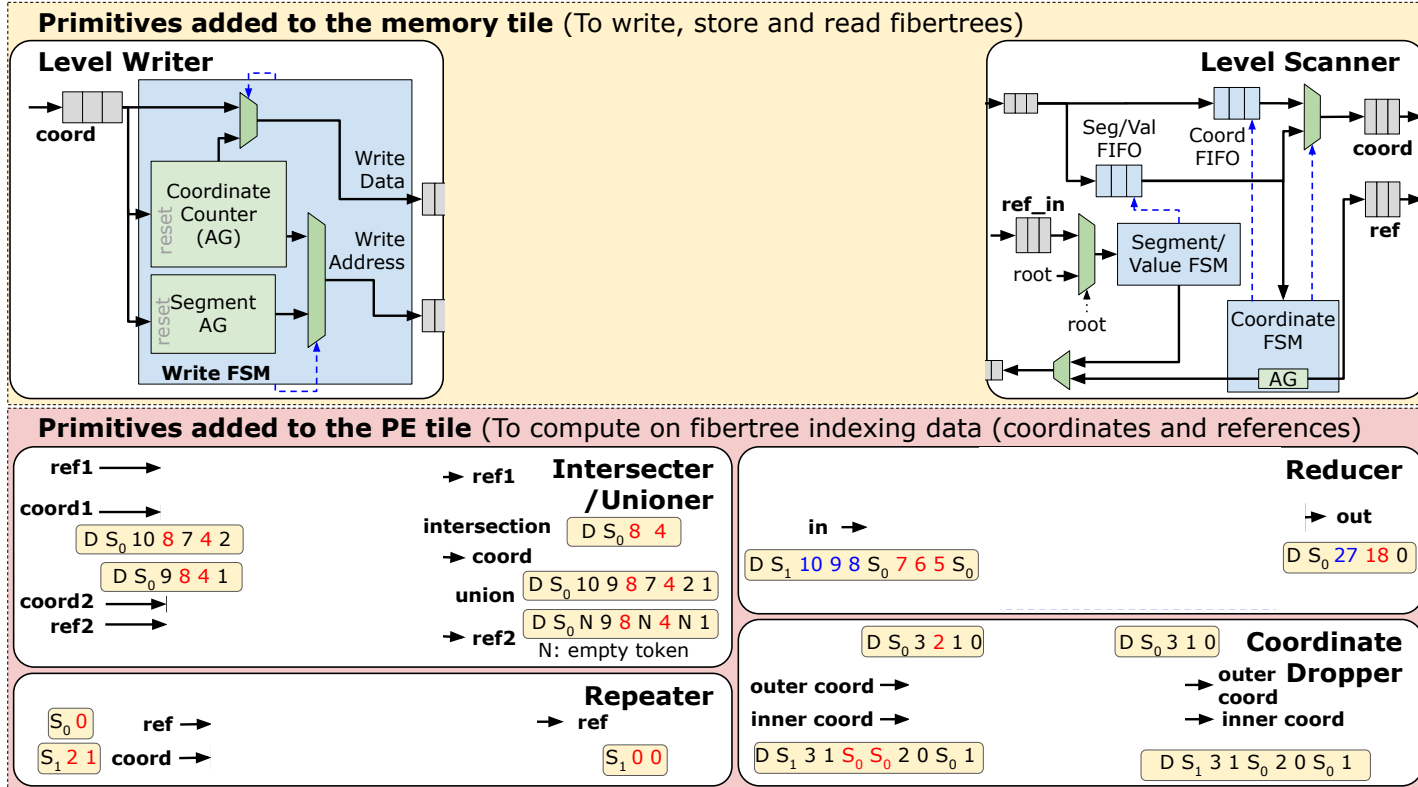
SAM as the architectural specification of our sparse CGRA fabric



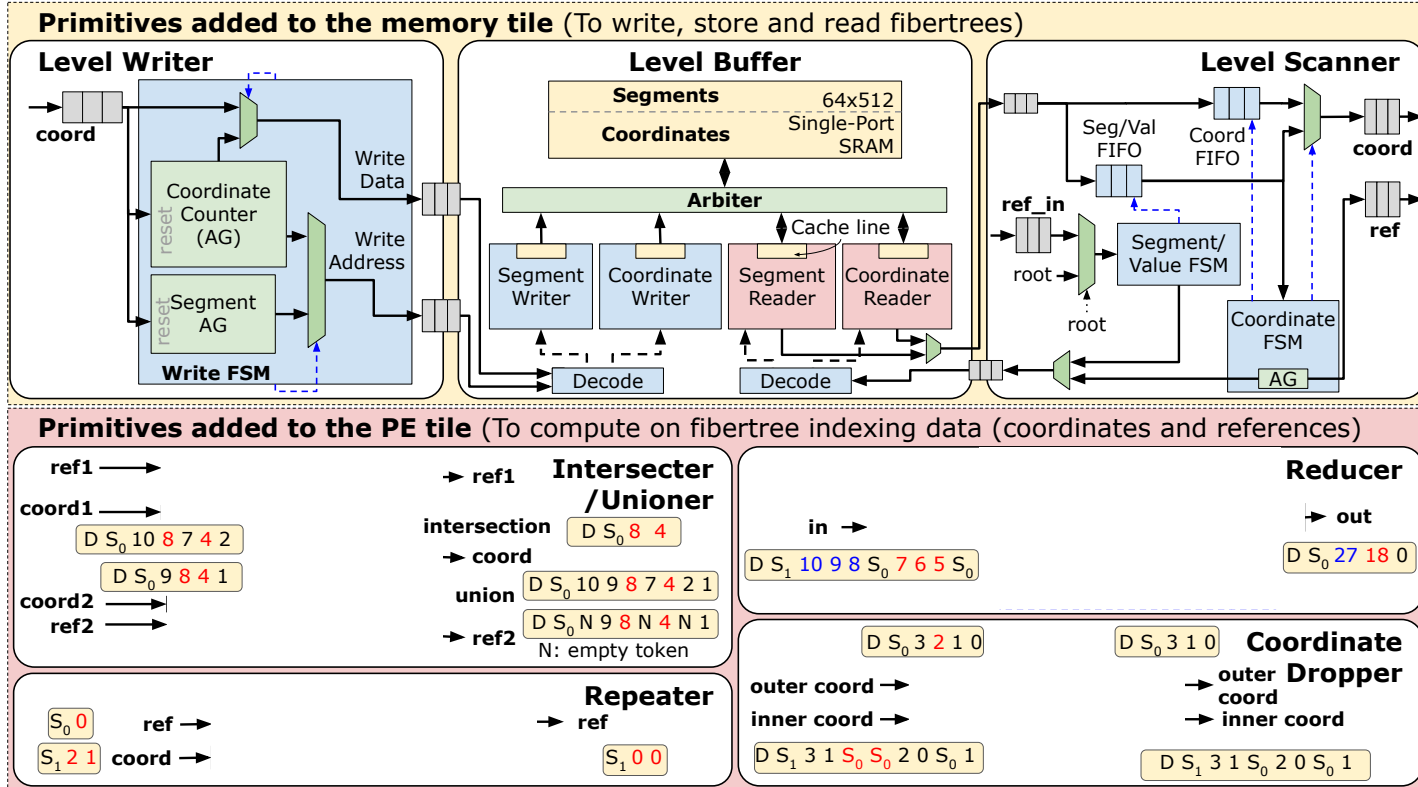
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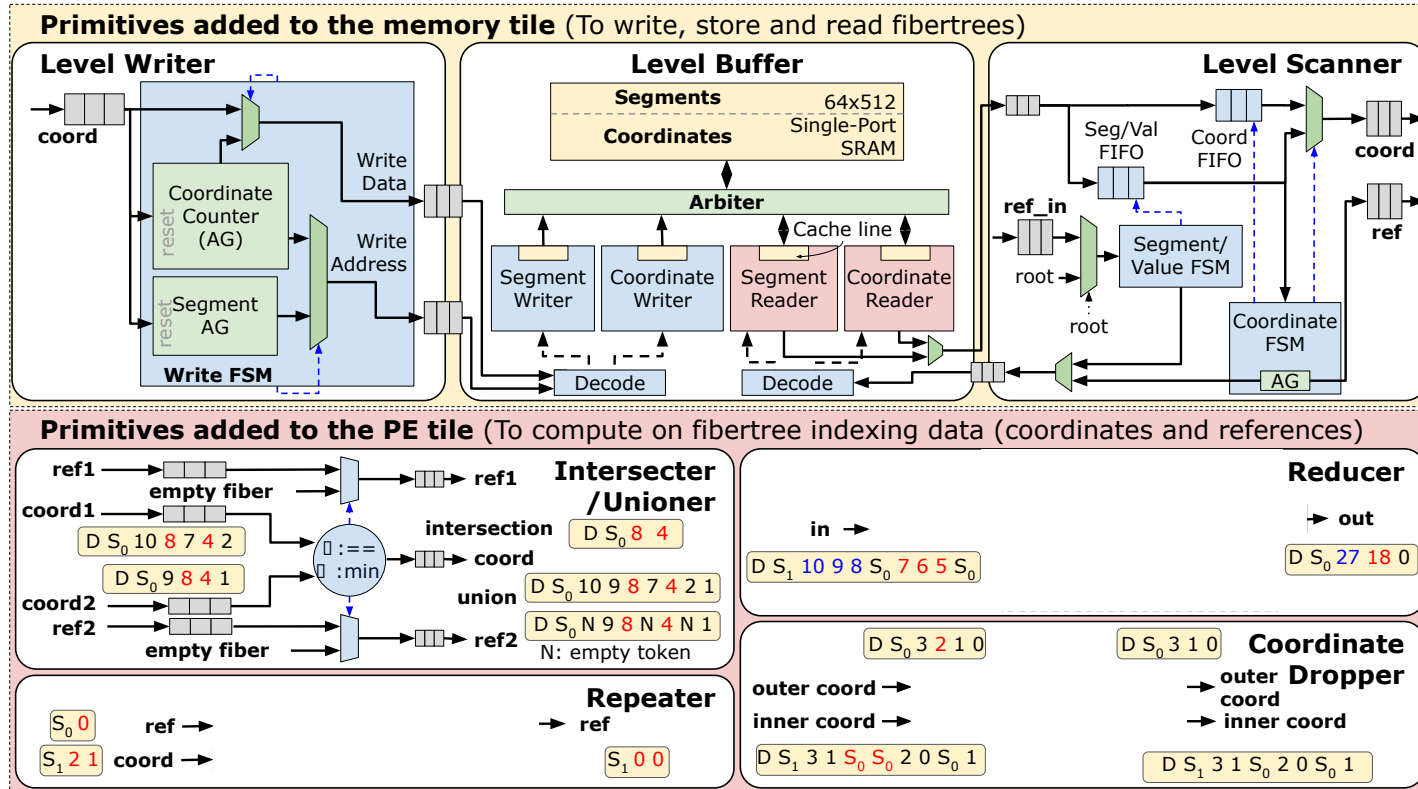
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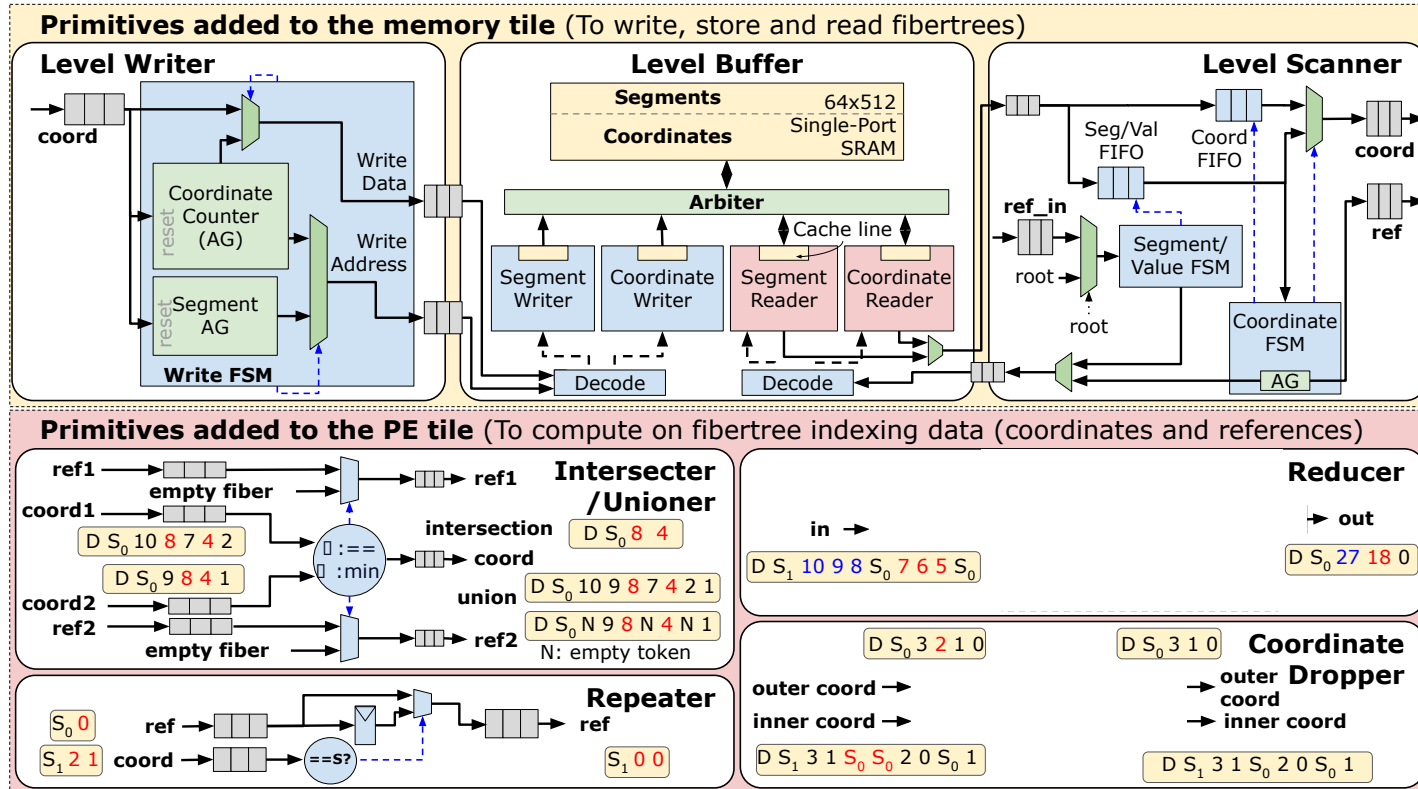
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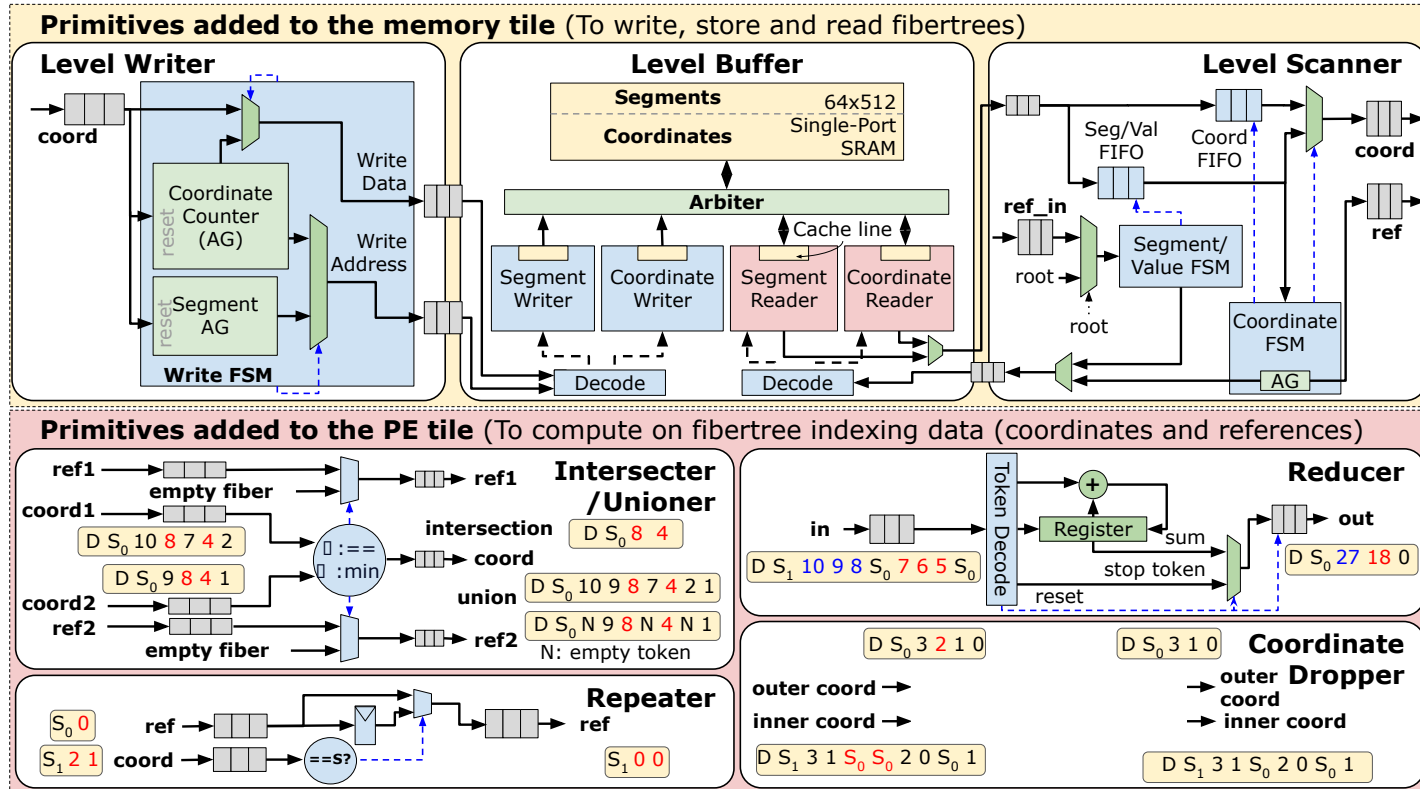
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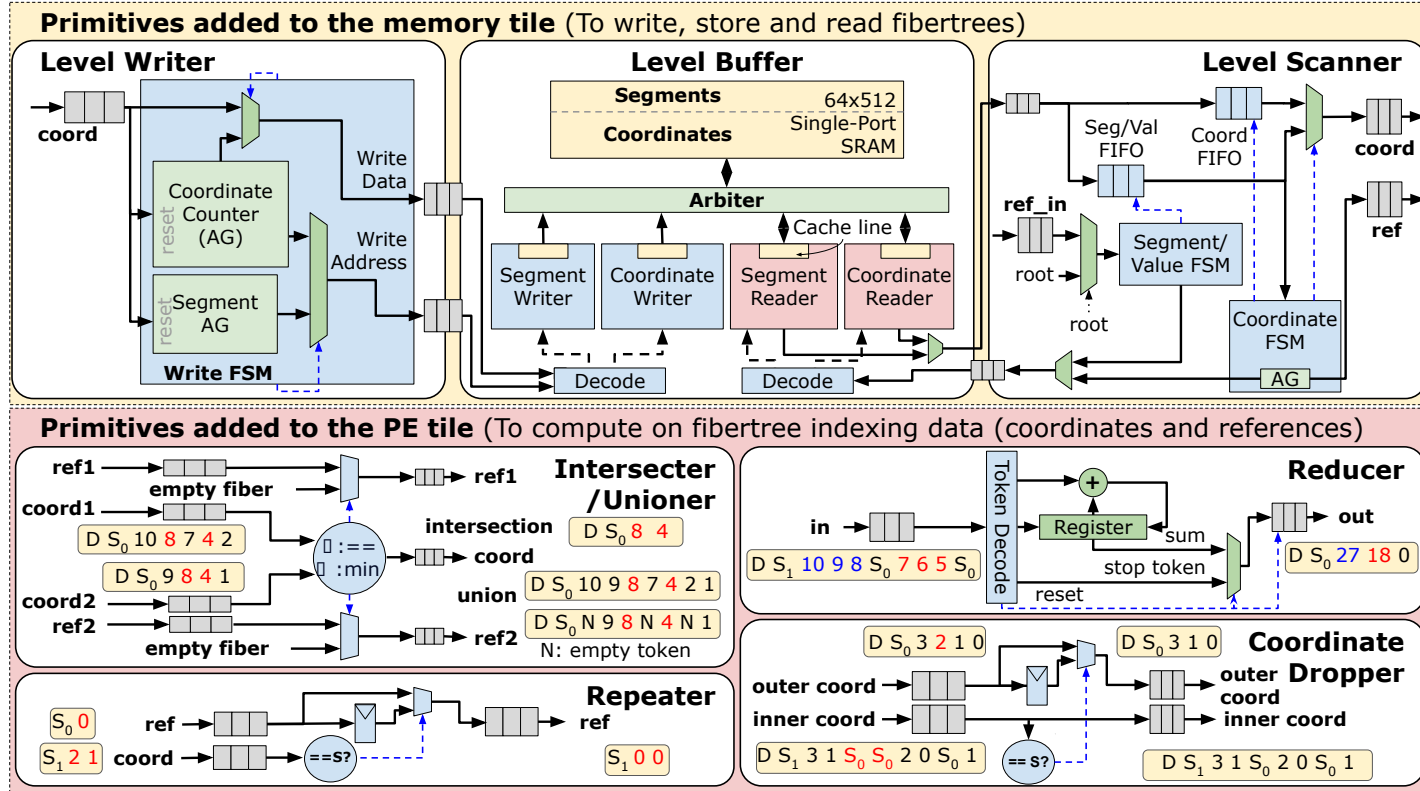
SAM as the architectural specification of our sparse CGRA fabric



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SAM as the architectural specification of our sparse CGRA fabric



Hardware-aware sparse dataflow graph

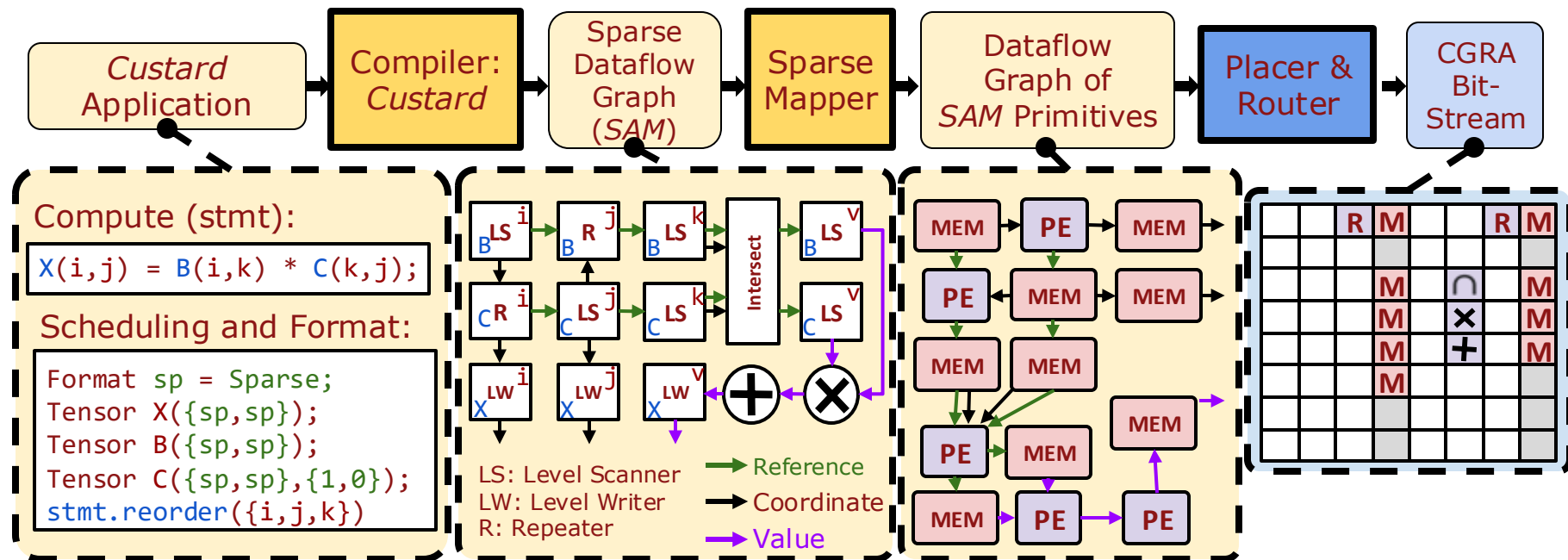
- CGRA architecture and microarchitecture requires more transformations during binding
- Introduce the concept of a hardware-aware SAM graph
- Performs transformations like:
 - Broadcast removal
 - Decomposition of N-joiners to binary joiners
 - Merges Level Scanners and Level Writers
 - Inserts Level Buffers

Demo: Mapping to CGRA Microarchitecture

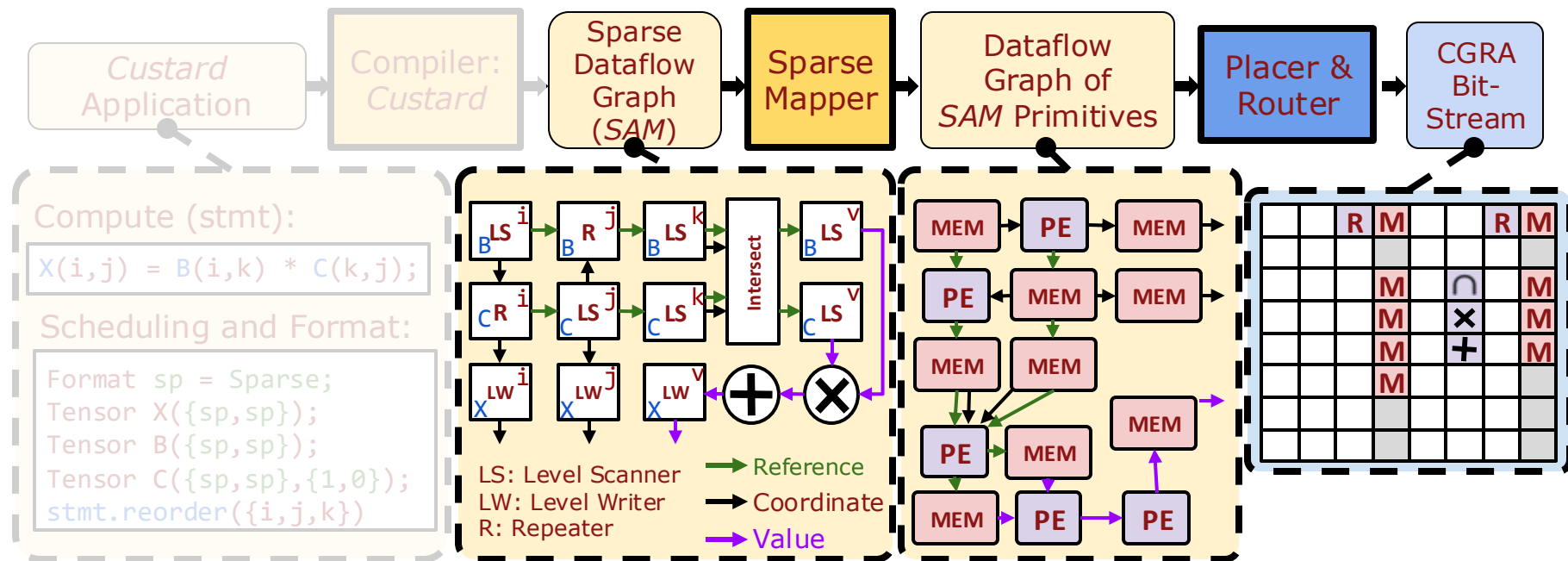
```
> ./sparse_demo.sh lower
```

- This runs the SAM graph through the lowering process to produce a hardware-aware sparse dataflow graph
- We can visualize that graph in
`/aha/sam/hw_aware_mat_elemadd.png`

Tool flow that maps SAM to a CGRA



Tool flow that maps SAM to a CGRA



Demo: Generating CGRA Bitstream for sparse applications

Run the following command:

```
> ./sparse_demo.sh gen
```

- This generates a CGRA bitstream from the hardware-aware graph using tools introduced later
- It also generates a testbench that runs an example matrix through, checking it with gold (written in Numpy)
- Explore output files generated in
`/aha/garnet/SPARSE_TESTS/mat_elemadd_0/`

- Dataflow hardware, like CGRAs, can speed up sparse computation
- Presented ideas from the Sparse Abstract Machine and Onyx
 - SAM is an abstract IR that represents sparse tensor algebra as dataflow graphs
 - SAM comes with the Custard front-end compiler
- Introduced the AHA flow for sparse applications

Conclusion