



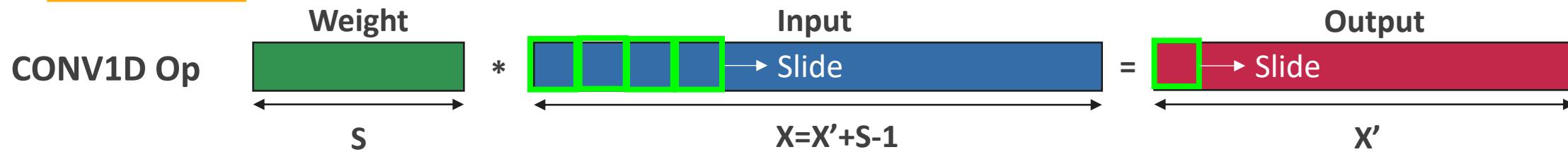
A High-level Overview of MAESTRO Mapping Directives and Cost Model

Synergy Lab, Georgia Tech
Hyoukjun Kwon

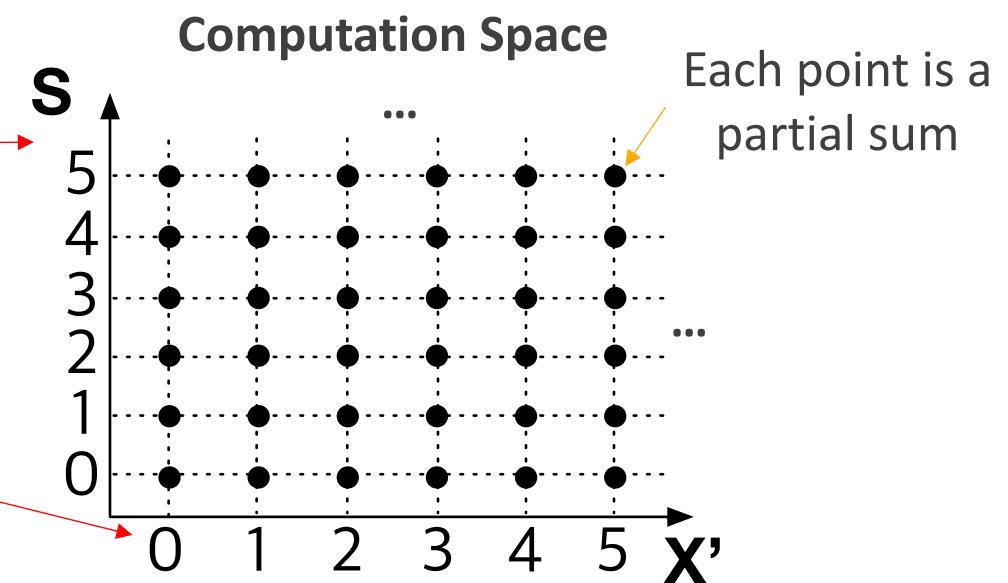
Outline

- 
- **Mapping Representation: A data-centric representation**
 - Computation and Data Space
 - Data-centric Directives
 - Deep-dive Example: Eyeriss-like Dataflow
 - **MAESTRO Cost Model – High Level Overview**

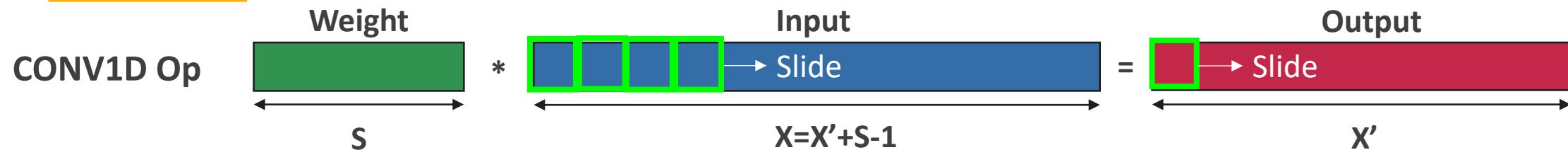
Computation Space of CONV1D



```
for(int s = 0; s < S; s++)  
for(int x' = 0; x' < X'; x'++)  
    PartialSum[x'][s] = Weight[s] * Input[x'+s]  
    Output[x'] += PartialSum[x'][s]
```



Data Space of CONV1D

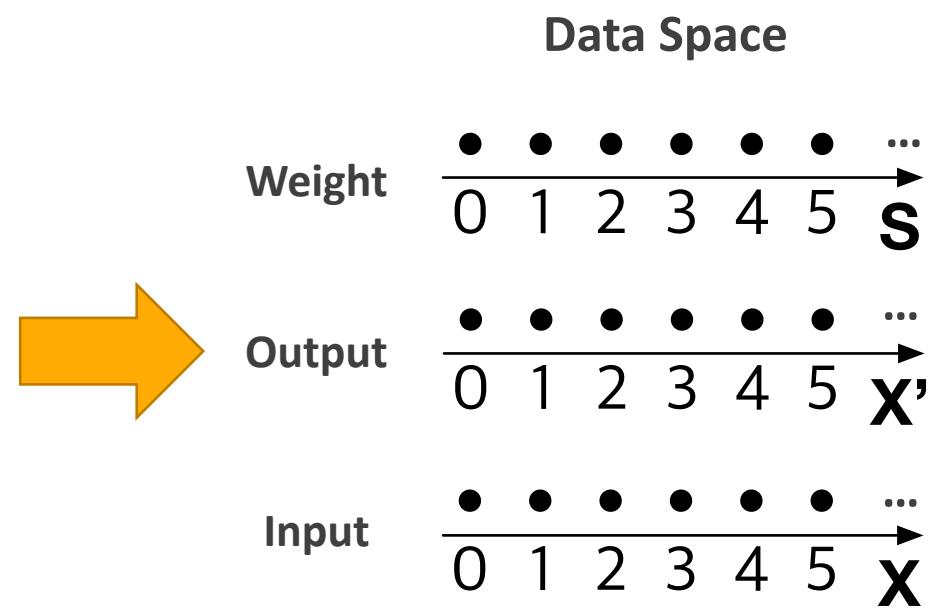


```

for(int s = 0; s < S; s++)
  for(int x' = 0; x' < X'; x'++)
    PartialSum[x'][s] = Weight[s] * Input[x'+s]
    Output[x'] += PartialSum[x'][s]
  
```

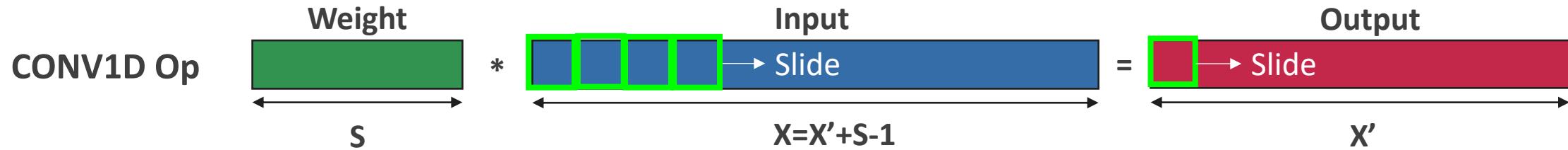
PartialSum[x'][s]
needs to access:

- Weight[s]
- Output[x']
- Input[x'+s]



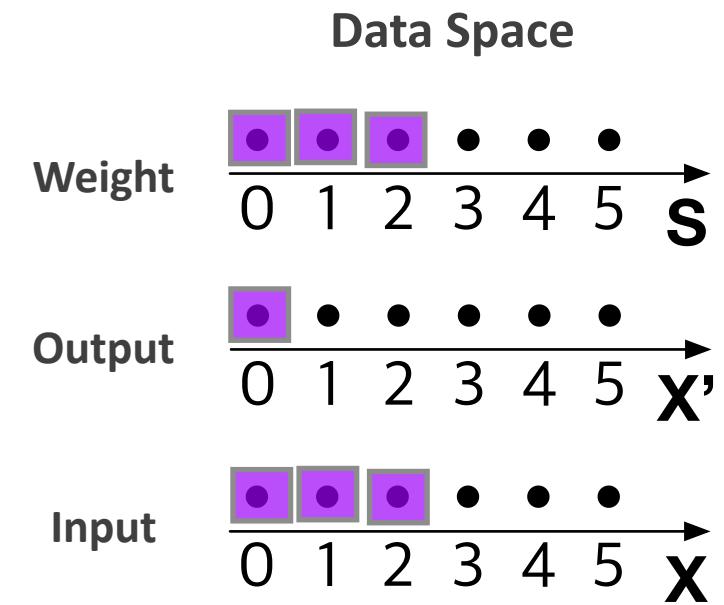
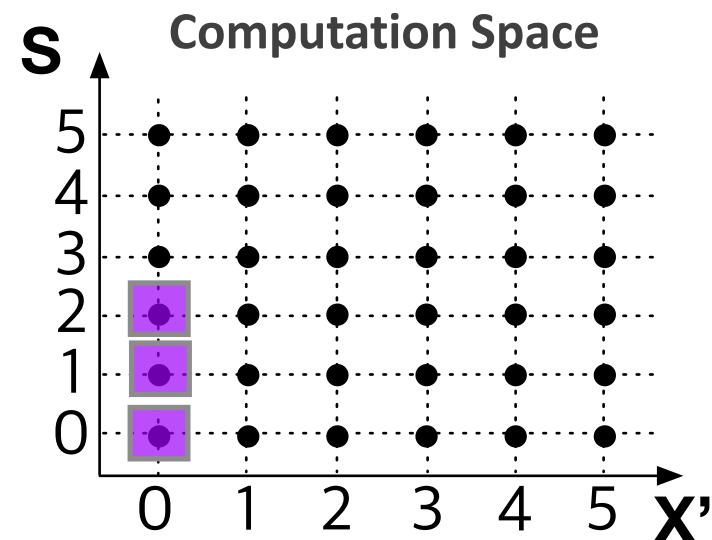
Data reuse is behavior in data space!

Computation and Data Space



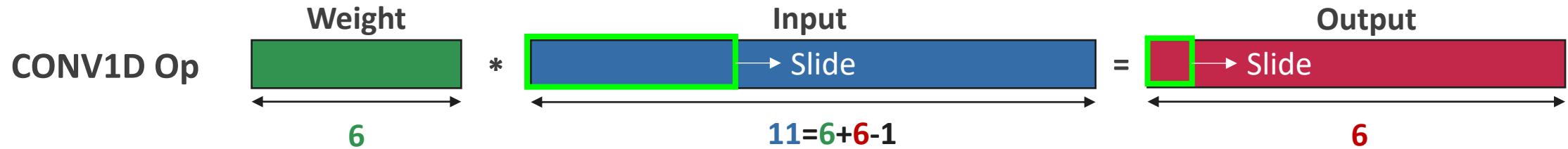
PartialSum[x'][s]
needs to access:

- Weight[s]
- Output[x']
- Input[x'+s]

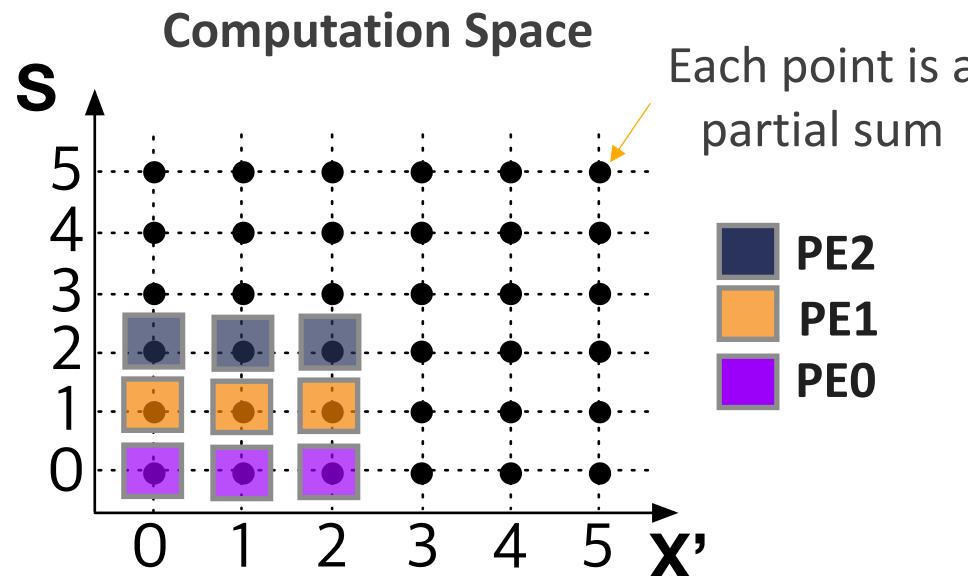


Partial sum has 1:1 correspondence to each data tensor

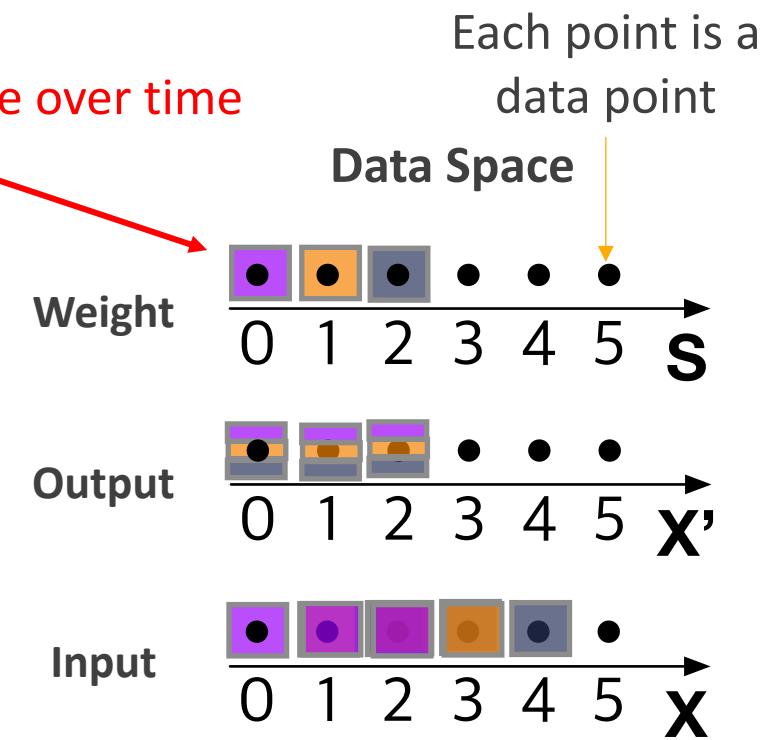
Mapping Example 1: Weight Stationary



Time = 0



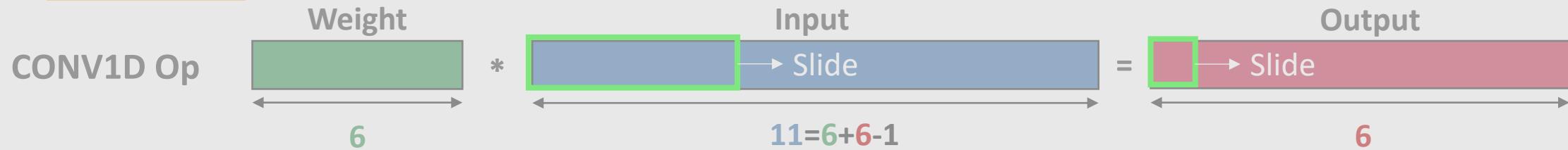
Weight does not change over time



- PartialSum[x'][s]
needs to access:
- Weight[s]
 - Output[x']
 - Input[$x' + s$]

"Weight Stationary" Dataflow

Mapping Example 2: Output Stationary



Time = 0

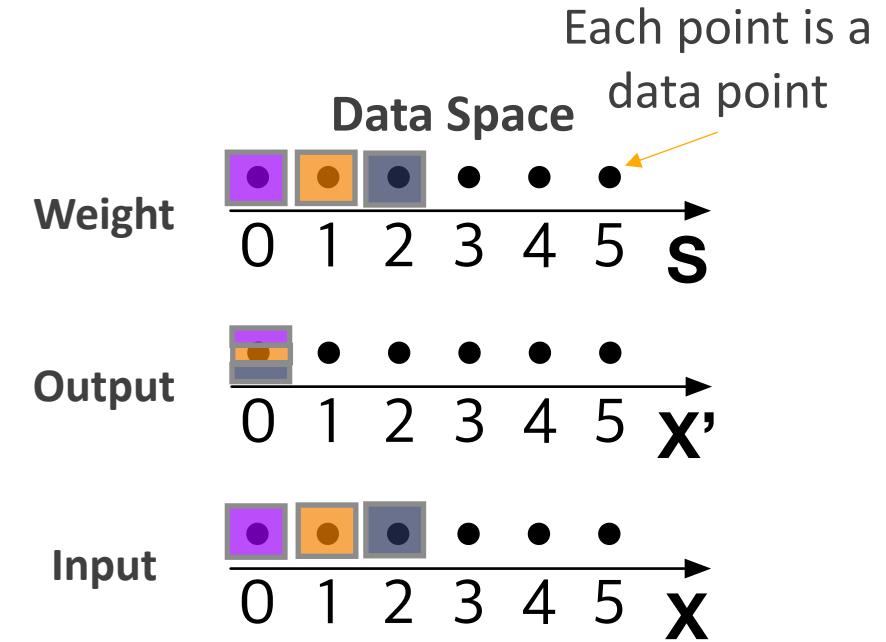
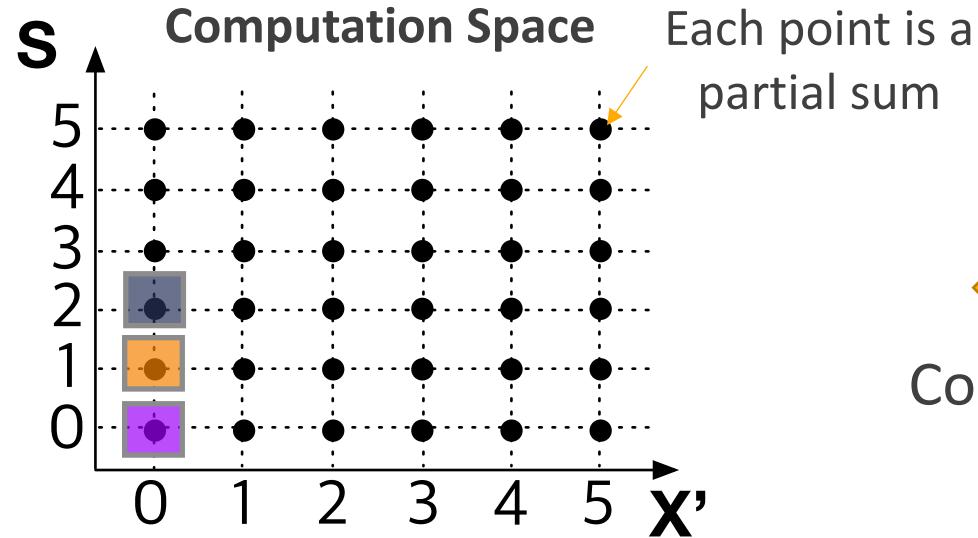
Output does not change over time

Each point is a data point



“Output Stationary” Dataflow

Computation and Data Space



- Describes computations (What it does)
- Higher dimensionality than data (CONV2D: 7D loop nest)
- Easy for programmers to understand
- Representation: *Loop nest*
- Directly describes data mapping (What it uses)
- Good to be used as an IR for tools (intermediate representation)!
- Easy for tools to analyze data reuse
- Representation: ??

How do we describe data space?

Outline

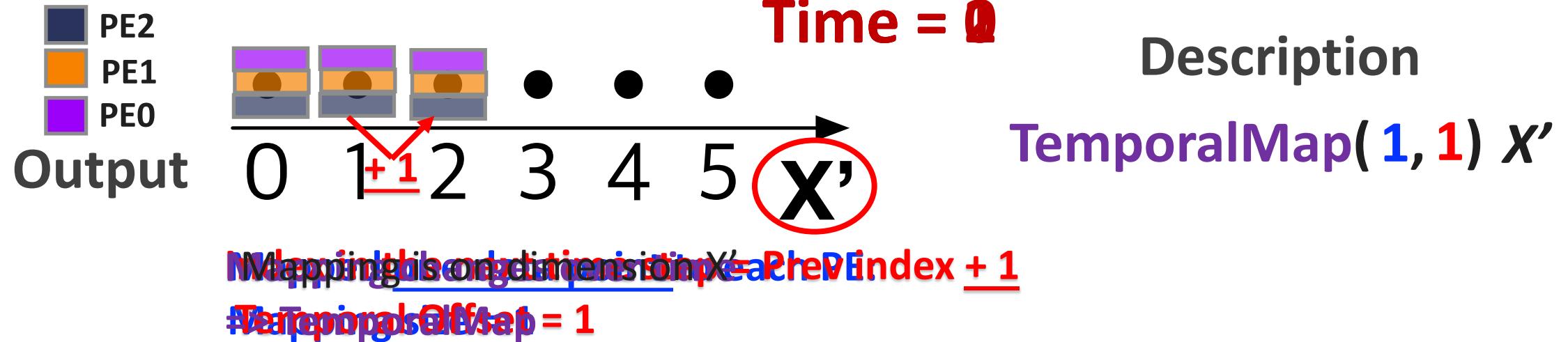
- **Mapping Representation: A data-centric representation**
 - Computation and Data Space
 - Data-centric Directives
 - Deep-dive Example: Eyeriss-like Dataflow
- **MAESTRO Cost Model – High Level Overview**



Introducing Data-centric Directives

▪ Temporal Map

Syntax: `TemporalMap(Mapping size, Temporal Offset) Dim`



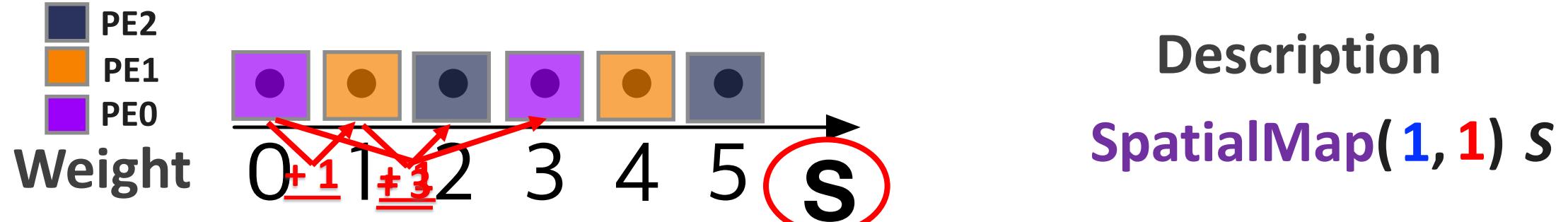
- **High-level Semantics:** Map the same data* across PEs, and update the mapping over time

* When the data dimension is not 1D, maps a dimension of data, not data points

Introducing Data-centric Directives

▪ Spatial Map

Syntax: `SpatialMap(Mapping size, Spatial Offset) Dim`

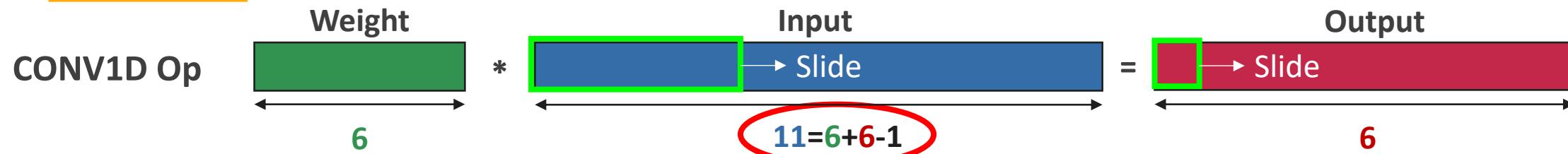


Description
`SpatialMap(1, 1) S`

- **High-level Semantics:** Map different data* across PEs with offset → **Parallelization!**
- **Spatial Folding:** When the number of PEs is not sufficient to cover entire data
 - **Implicit temporal offset:** the number of PEs

* When the data dimension is not 1D, maps a dimension of data, not data points

Describing Dataflows using Data-centric Directives



Syntax: **Sp/TpMap (Mapping size, Sp/Tp Offset) Dim**

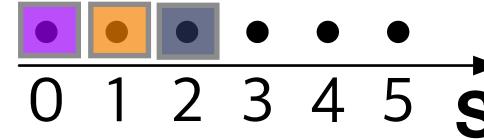
PE2
PE1
PE0

Data Space

Time = 0

What changes faster?

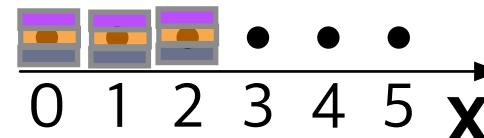
Weight



SpatialMap(1,1) S

Description

Output



TemporalMap(1,1) X'

Change slower

Input

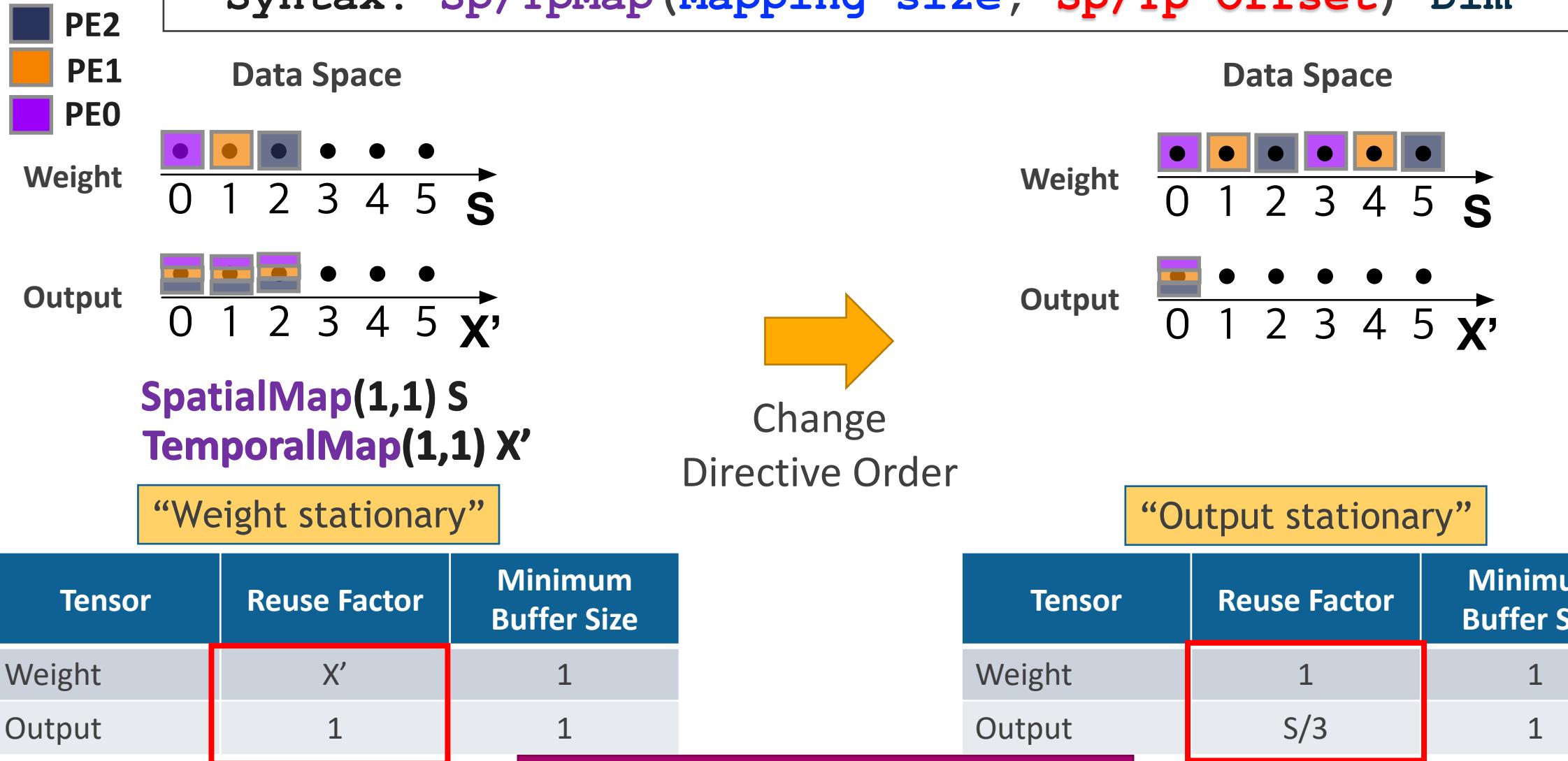


Change faster

Directive order: relative order of “change” in each data dimension

The Impact of Directive Order

Syntax: `Sp/TpMap (Mapping size, Sp/Tp Offset) Dim`



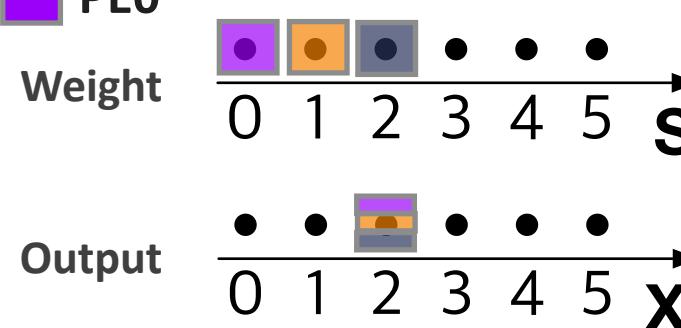
* Reuse factor: The number of acc

Weight Reuse to Output Reuse

The Impact of Spatial/Temporal Directive Choice

PE2
PE1
PE0

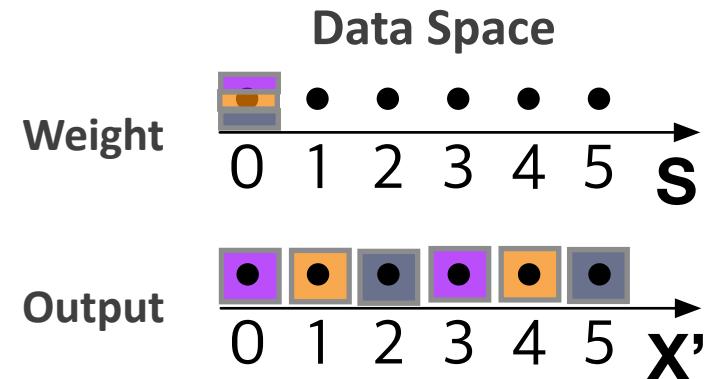
Data Space



SpatialMap(1,1) S
TemporalMap(1,1) X'

“Weight stationary”

Change
Spatial/Temporal



TemporalMap(1,1) S
SpatialMap(1,1) X'

“Weight stationary”

Tensor	Reuse Factor	Minimum Buffer Size
Weight	X'	1
Output	1	1

Tensor	Reuse Factor	Minimum Buffer Size
Weight	$X'/3$	1
Output	1	1

* Reuse factor: The number o

Different Weight-Stationary!

The Impact of Mapping Size

Syntax: `Sp/TpMap (Mapping size, Sp/Tp Offset) Dim`

PE2
PE1
PE0

Data Space

Weight

Even in a simple CONV1D, we observe complex trade-off space based on dataflow

Output

Data Space

“Weight stationary”

Directives can precisely describe dataflows

Mapping size

“Weight stationary”

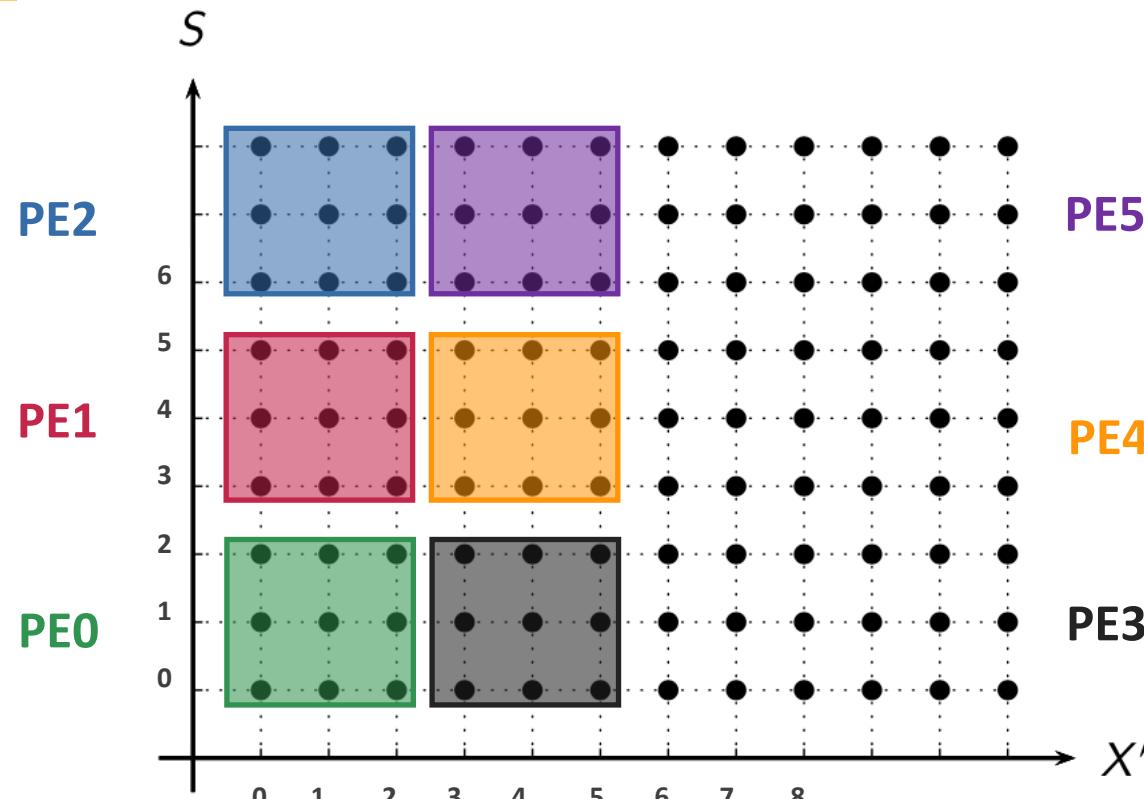
Tensor	Reuse Factor	Minimum Buffer Size
Weight	X'	1
Output	1	1

Tensor	Reuse Factor	Minimum Buffer Size
Weight	$X'/3$	1
Output	1	3

* Reuse factor: The number o

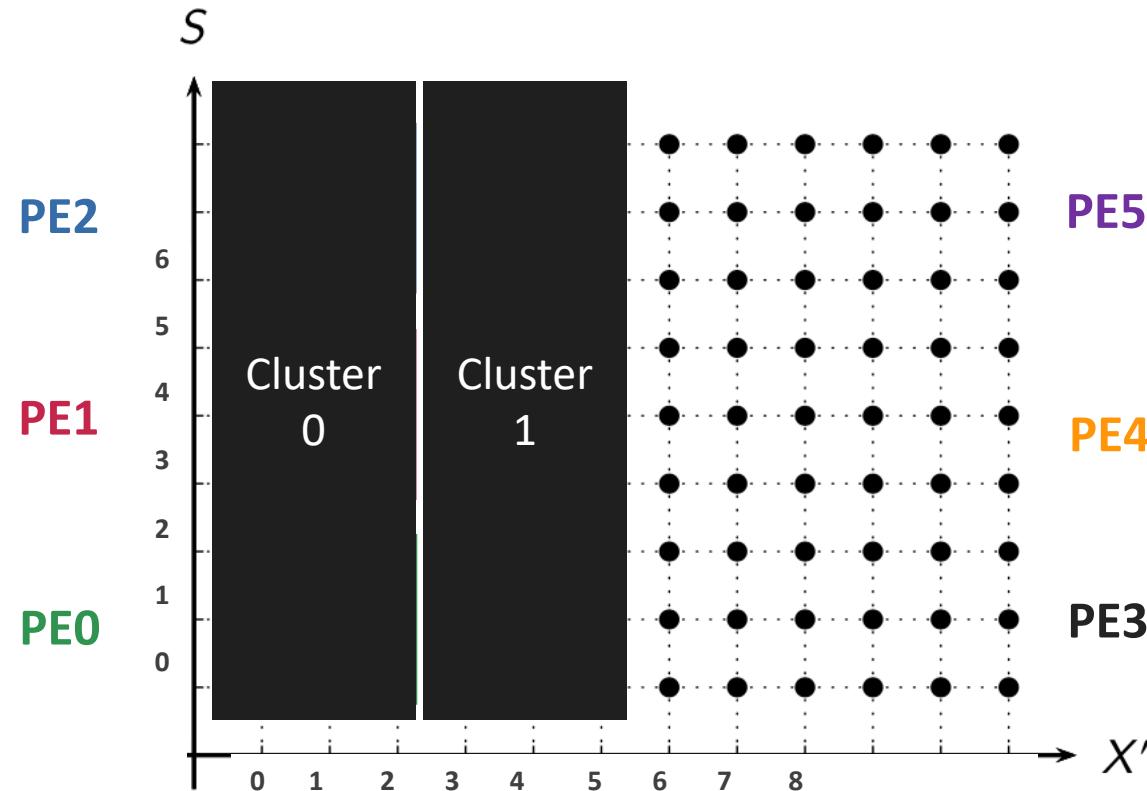
Another Weight-Stationary!

Describing Mappings with Multiple Parallel Dimensions



How to describe this dataflow?

Multi-level Parallelism via Clustering

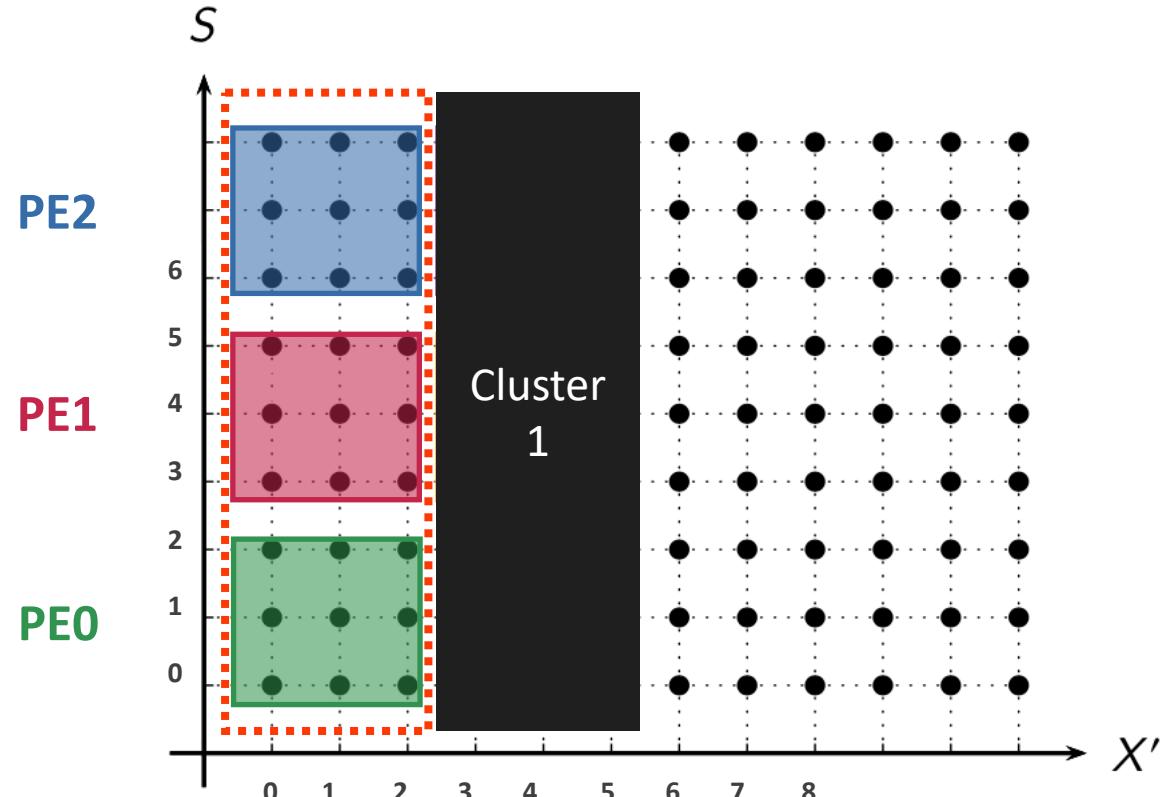


`TemporalMap(size=9, offset=9) S`

`SpatialMap(size=3, offset=3) X'`

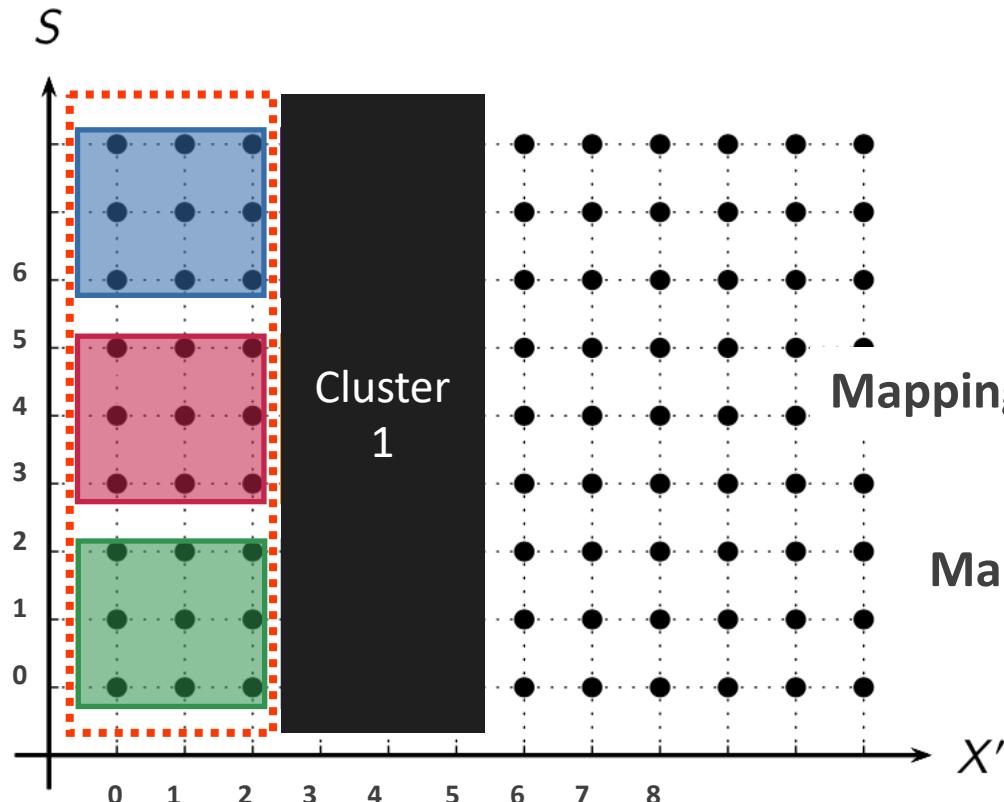
Mapping target: Clusters!

Multi-level Parallelism via Clustering



SpatialMap(size=3, offset=3) S
TemporalMap(size=3, offset=3) X'
Mapping target: PEs!

Multi-level Parallelism via Clustering



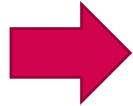
Mapping target: Clusters

Mapping target: PEs

- $\left\{ \begin{array}{l} \text{Temporal_Map(size=9, offset=9)} \ S \\ \text{Spatial_Map(size=3, offset=3)} \ X' \\ \text{Cluster (size=3)} \end{array} \right.$
- $\left\{ \begin{array}{l} \text{Spatial_Map(size=3, offset=3)} \ S \\ \text{Temporal_Map(size=3, offset=3)} \ X' \end{array} \right.$

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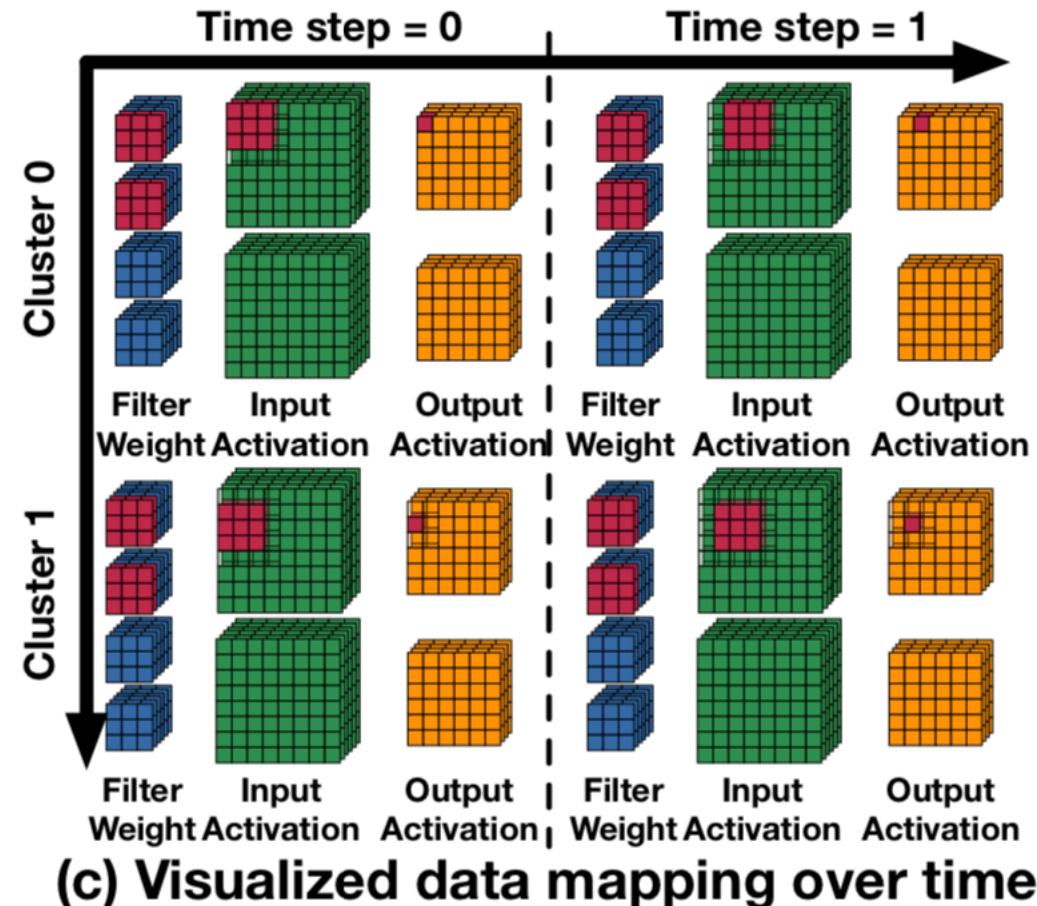


Full CONV2D Mapping Overview (Eyeriss-like)

TemporalMap(1,1) N
TemporalMap(2,2) K
TemporalMap(3,3) C
SpatialMap(3,1) Y
- **TemporalMap**(3,1) X
Cluster(3, L)
SpatialMap(1,1) Y
* **SpatialMap**(1,1) R
* **TemporalMap**(3,3) S

* Dimension Fully Covered by One Iteration

(b) Example dataflow



Eyeriss-like Mapping

Free Variables

TemporalMap($\text{TileSz}(K), \text{TileSz}(K)$) K

TemporalMap($\text{TileSz}(C), \text{TileSz}(C)$) C

SpatialMap($\text{Sz}(R), 1$) Y

TemporalMap($\text{Sz}(S), 1$) X

Cluster($\text{Sz}(R)$) 2D PE array

SpatialMap($1, 1$) Y

SpatialMap($1, 1$) R

TemporalMap($\text{Sz}(S), \text{Sz}(S)$) S

Eyeriss Hardware Implied by Mapping

- Will Assume 3x3 filter and 6 PEs in total

TemporalMap(2,2) K

TemporalMap(2,2) C

SpatialMap(3,1) Y

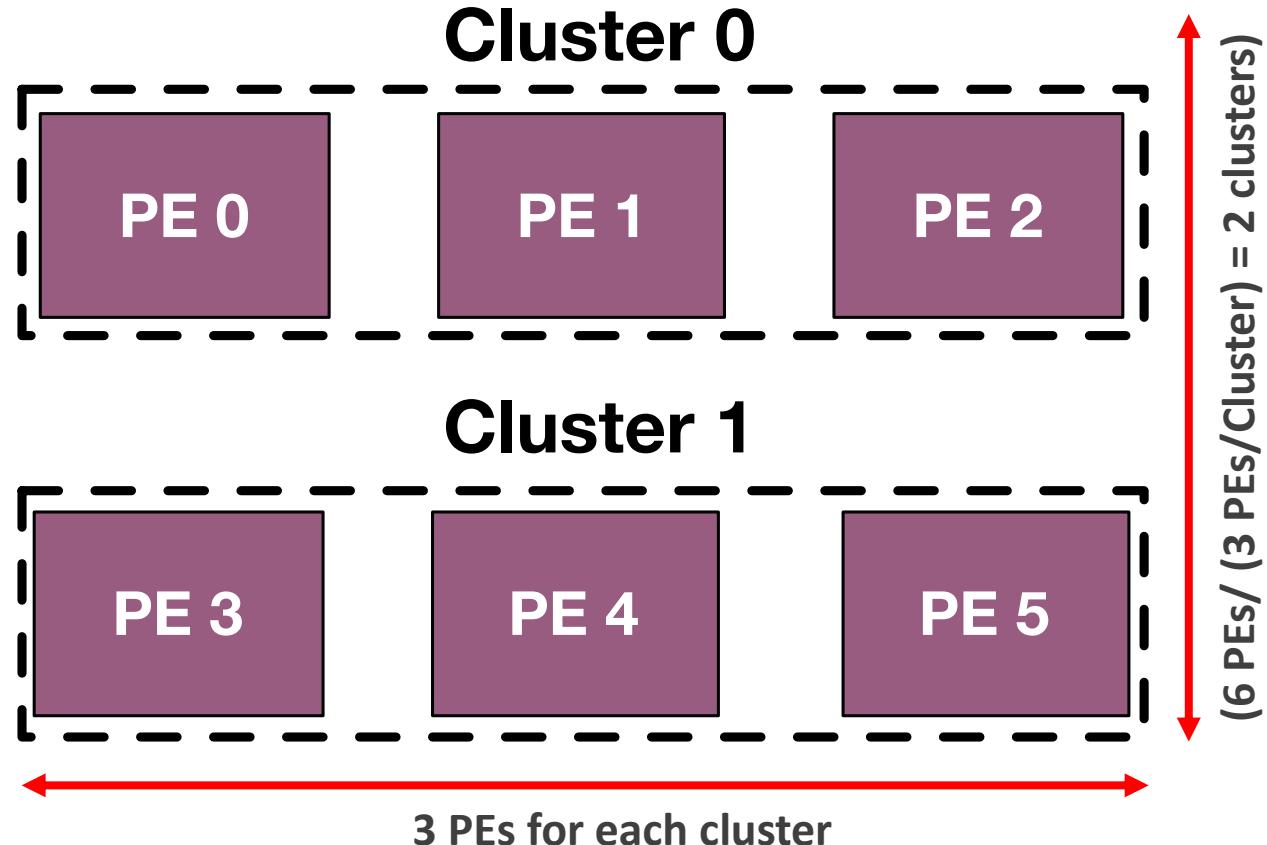
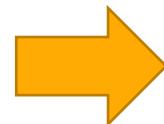
TemporalMap(3,1) X

Cluster(3)

SpatialMap(1,1) Y

SpatialMap(1,1) R

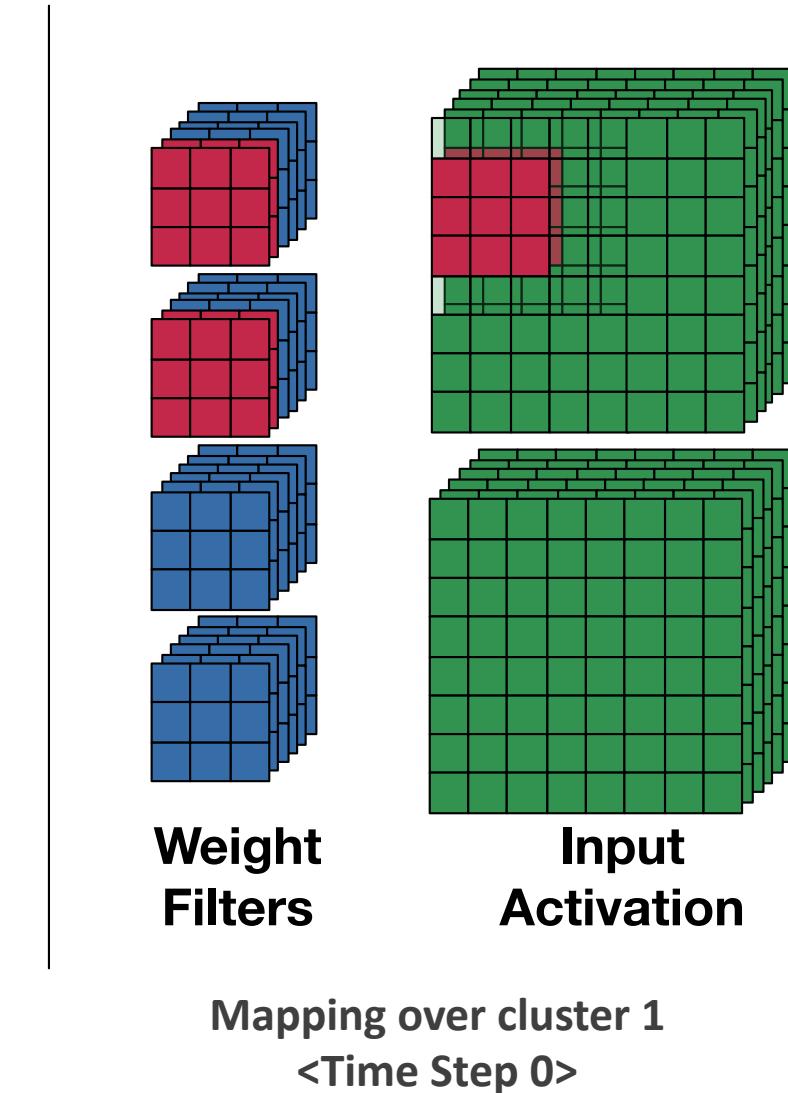
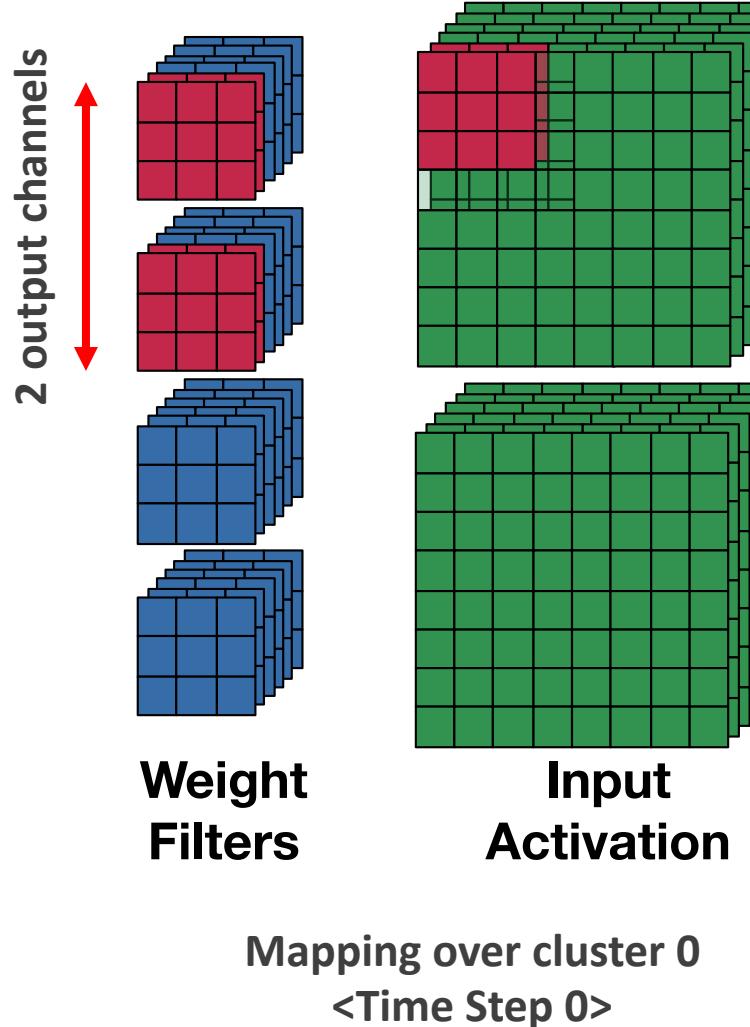
TemporalMap(3,3) S



Tile Size / Offset Analysis

TemporalMap (Map size, Offset) *Dim*
SpatialMap (Map size, Offset) *Dim*

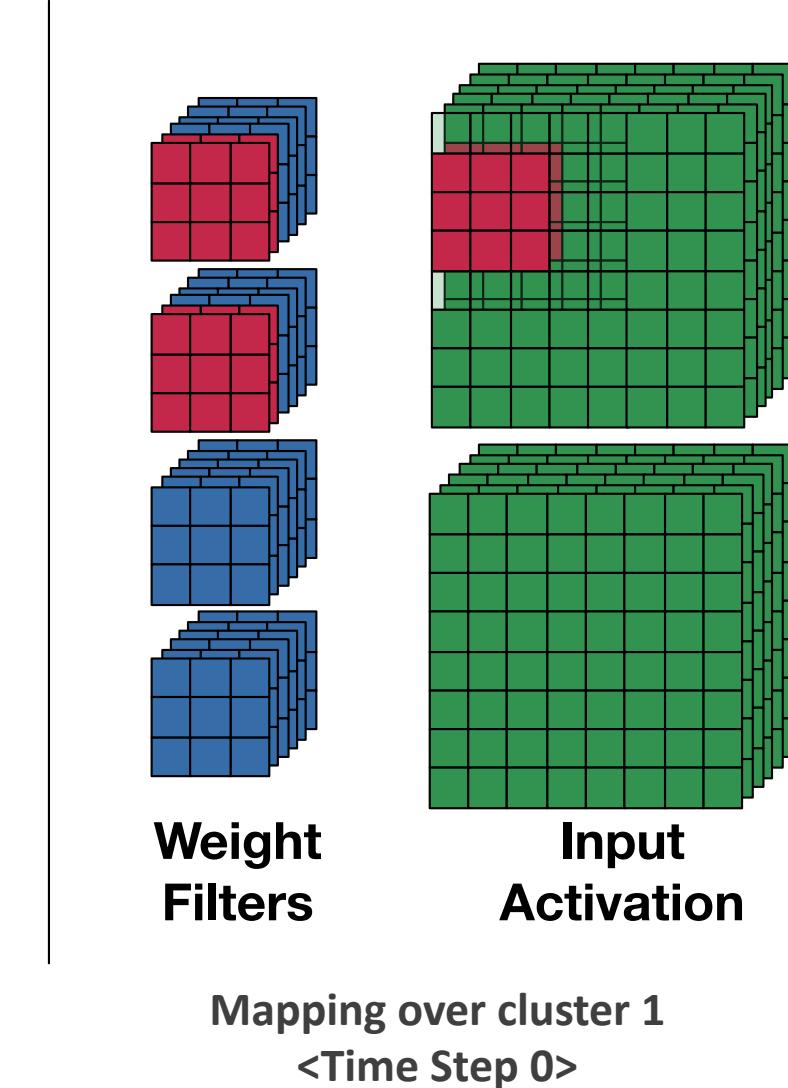
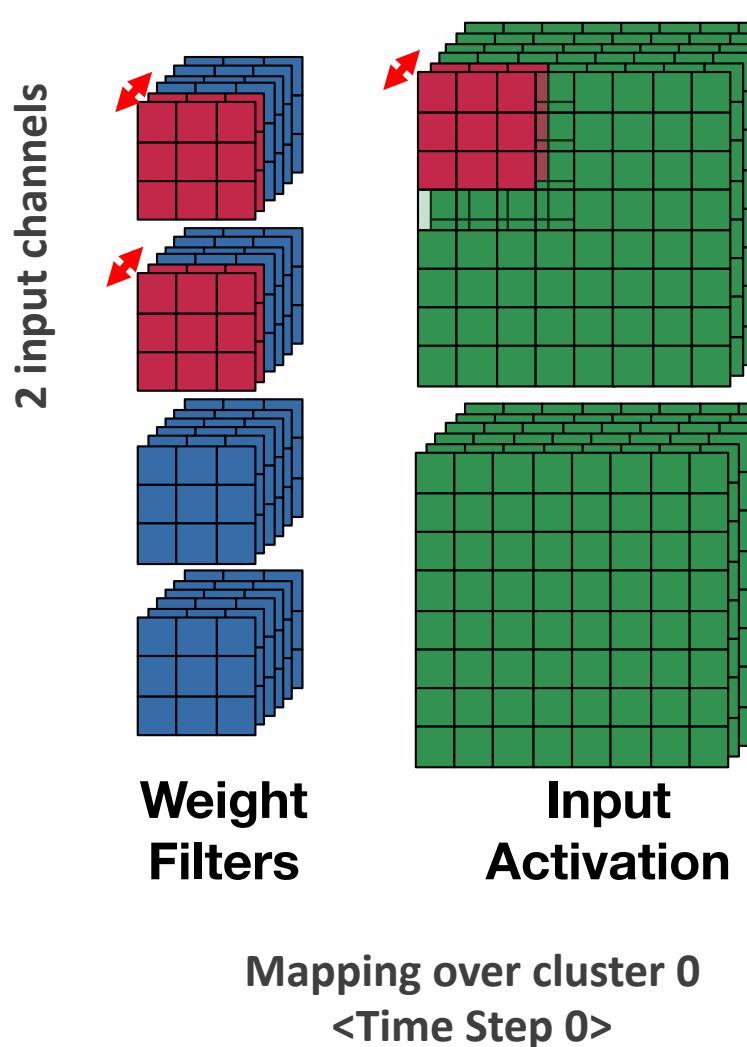
TemporalMap(2,2) K
TemporalMap(2,2) C
SpatialMap(3,1) Y
TemporalMap(3,1) X
Cluster(3)
SpatialMap(1,1) Y
SpatialMap(1,1) R
TemporalMap(3,3) S



Tile Size / Offset Analysis

TemporalMap (Map size, Offset) *Dim*
SpatialMap (Map size, Offset) *Dim*

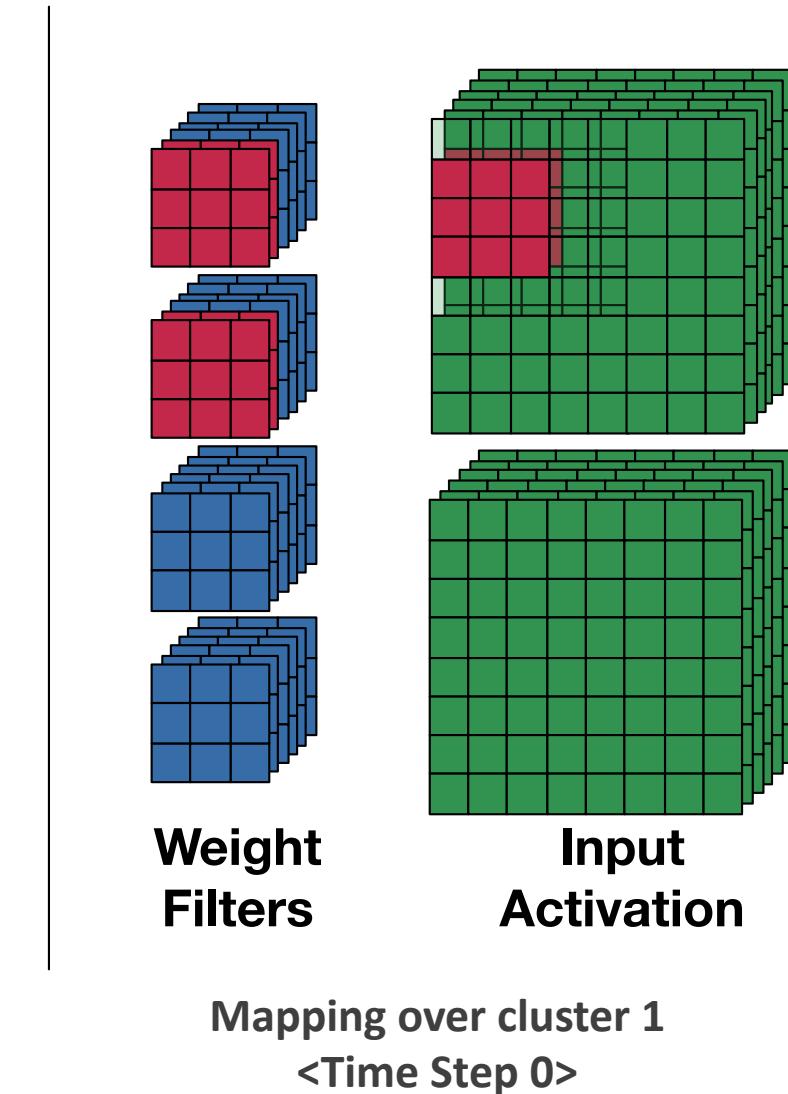
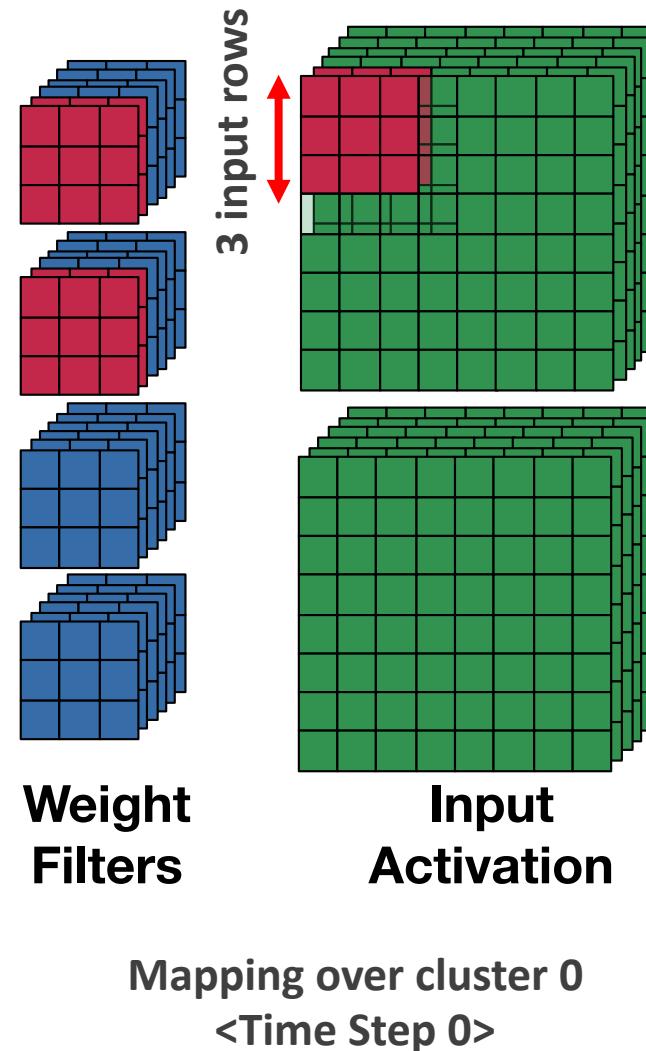
TemporalMap(2,2) K
TemporalMap(2,2) C
SpatialMap(3,1) Y
TemporalMap(3,1) X
Cluster(3)
SpatialMap(1,1) Y
SpatialMap(1,1) R
TemporalMap(3,3) S



Tile Size / Offset Analysis

TemporalMap (Map size, Offset) *Dim*
SpatialMap (Map size, Offset) *Dim*

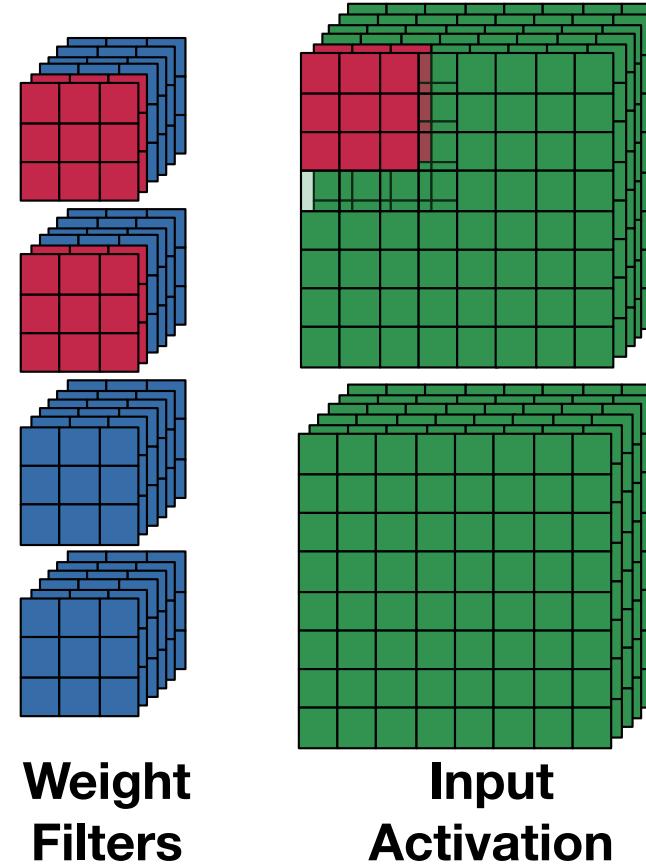
TemporalMap(2,2) K
TemporalMap(2,2) C
SpatialMap(3,1) Y
TemporalMap(3,1) X
Cluster(3)
SpatialMap(1,1) Y
SpatialMap(1,1) R
TemporalMap(3,3) S



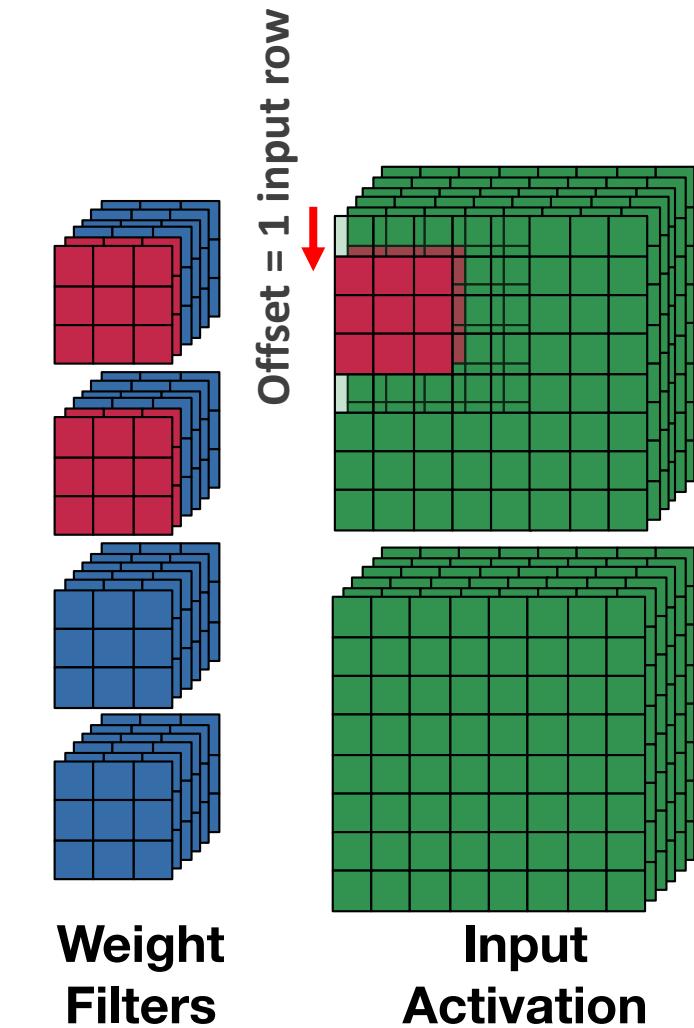
Tile Size / Offset Analysis

TemporalMap (Map size, Offset) *Dim*
SpatialMap (Map size, Offset) *Dim*

TemporalMap(2,2) K
TemporalMap(2,2) C
SpatialMap(3,1) Y
TemporalMap(3,1) X
Cluster(3)
SpatialMap(1,1) Y
SpatialMap(1,1) R
TemporalMap(3,3) S



Mapping over cluster 0
<Time Step 0>



Mapping over cluster 1
<Time Step 0>

Tile Size / Offset Analysis

TemporalMap (Map size, Offset) *Dim*
SpatialMap (Map size, Offset) *Dim*

■ Tile Size Analysis

TemporalMap(2,2) K

TemporalMap(2,2) C

SpatialMap(3,1) Y

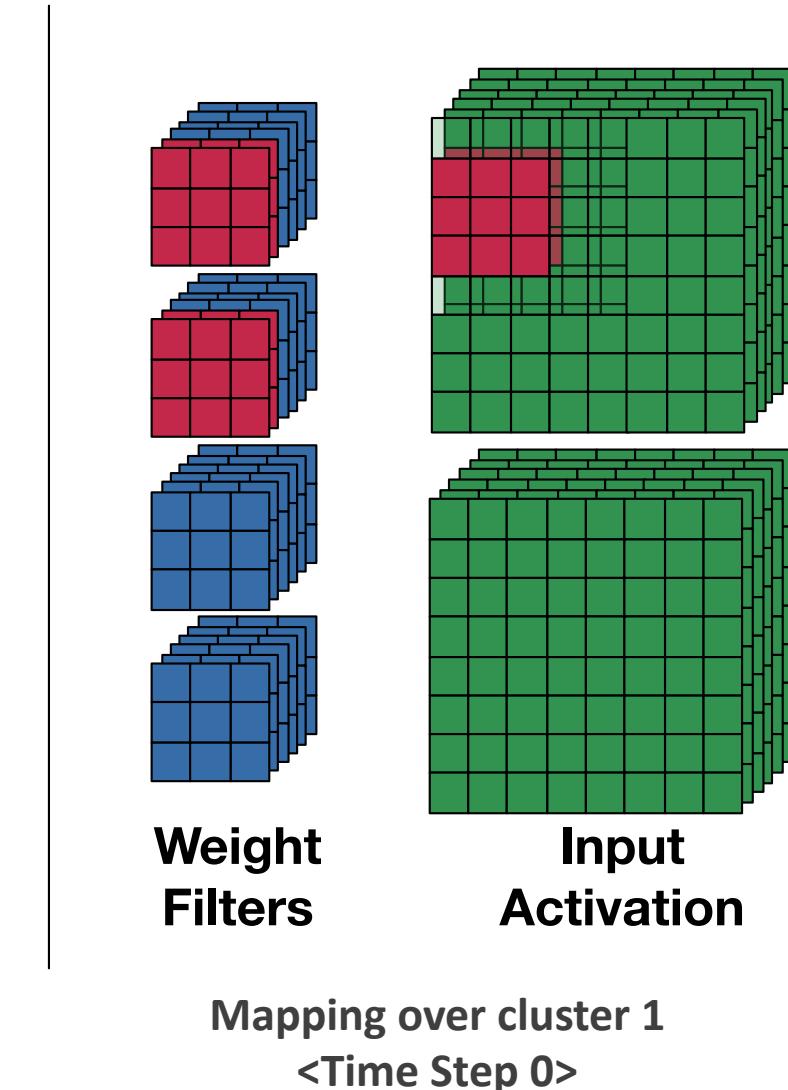
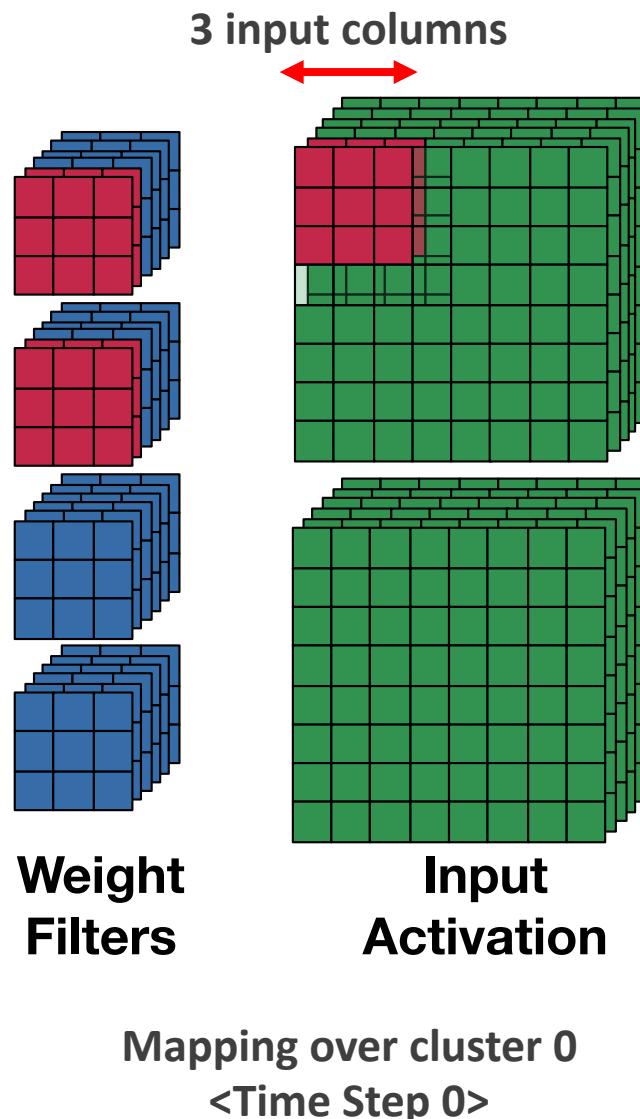
TemporalMap(3,1) X

Cluster(3)

SpatialMap(1,1) Y

SpatialMap(1,1) R

TemporalMap(3,3) S



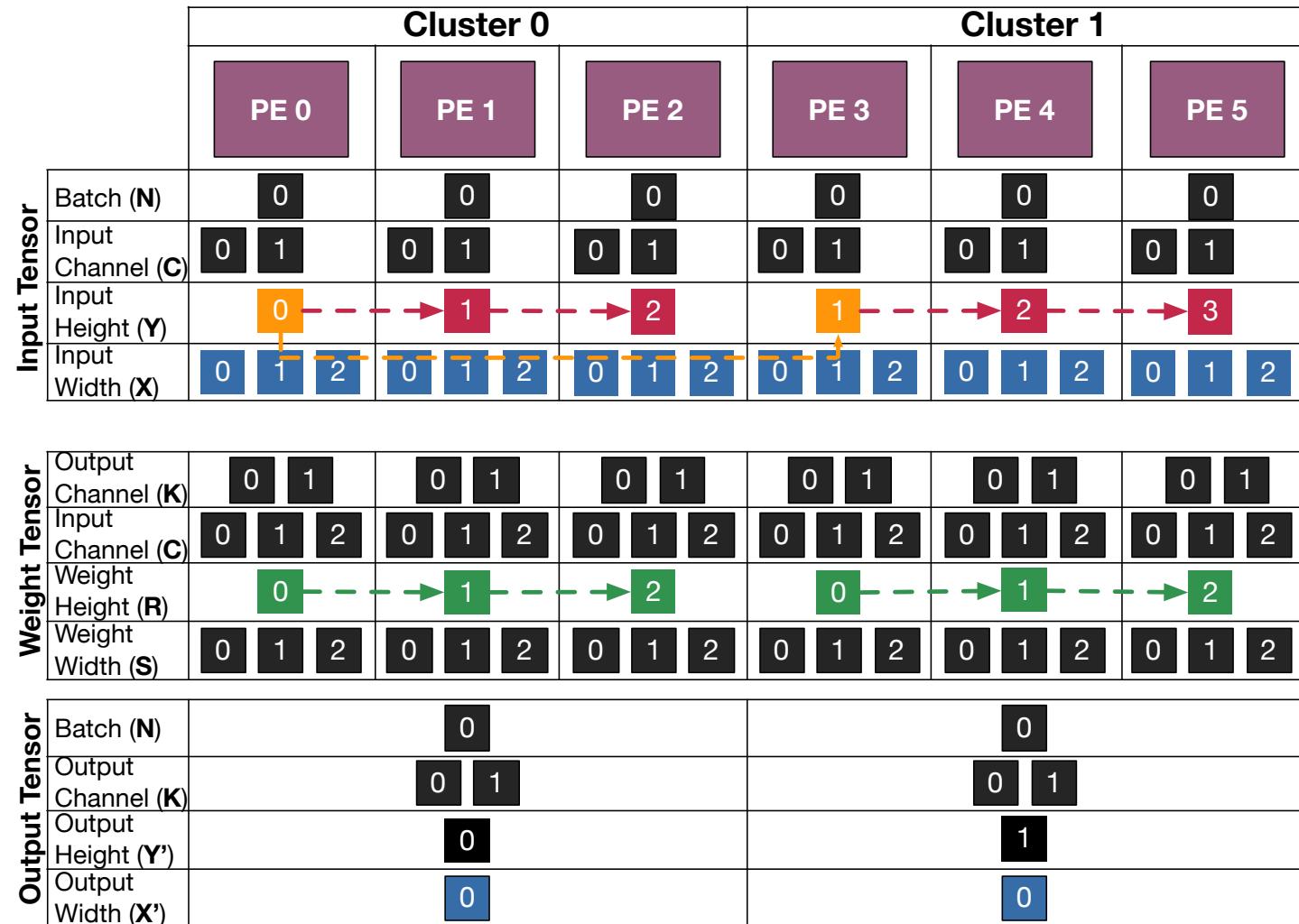
Data Reuse Analysis

TemporalMap (Map size, Offset) *Dim*
 SpatialMap (Map size, Offset) *Dim*

TemporalMap(2,2) K
TemporalMap(2,2) C
SpatialMap(3,1) Y
TemporalMap(3,1) X
Cluster(3)
SpatialMap(1,1) Y
SpatialMap(1,1) R
TemporalMap(3,3) S

Variable Data class	Output Channel (K)	Input Channel (C)	Filter Row (R)	Filter Column (S)	Input Row (Y)	Input Column (X)
Output Activation	X		X	X	X	X
Input Activation		X			X	X
Filter Weights	X	X	X	X		

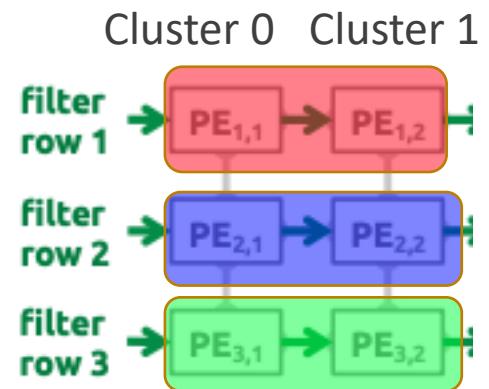
* Output row(Y') = Y-R+1, Output column(X') = X-S+1



<Time Step 0>

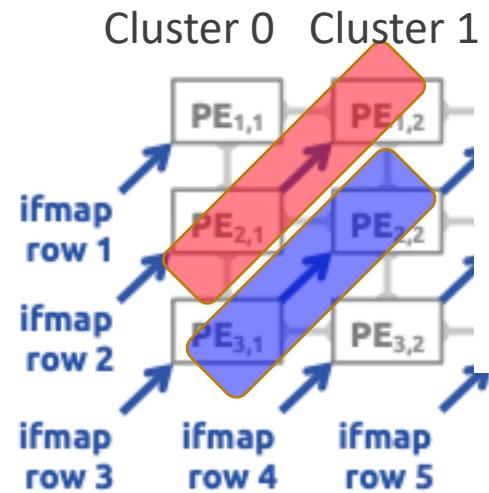
Data Reuse Analysis

		Cluster 0			Cluster 1		
Input Tensor	PE 0	PE 1	PE 2	PE 3	PE 4	PE 5	
	Batch (N)	0	0	0	0	0	0
	Input Channel (C)	0 1	0 1	0 1	0 1	0 1	0 1
	Input Height (Y)	0	1	2	1	2	3
	Input Width (X)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2
Weight Tensor	Output Channel (K)	0 1	0 1	0 1	0 1	0 1	0 1
	Input Channel (C)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2
	Weight Height (R)	0	1	2	0	1	2
	Weight Width (S)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2
	Batch (N)	0		0		0	
Output Tensor	Output Channel (K)	0 1		0 1		0 1	
	Output Height (Y')	0		1		0	
	Output Width (X')	0		0		0	



Data Reuse Analysis

Cluster 0			Cluster 1			
PE 0	PE 1	PE 2	PE 3	PE 4	PE 5	
Batch (N)	0	0	0	0	0	
Input Channel (C)	0 1	0 1	0 1	0 1	0 1	
Input Height (Y)	0	1 → 2	2	1 → 2	2 → 3	
Input Width (X)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	
Output Channel (K)	0 1	0 1	0 1	0 1	0 1	
Input Channel (C)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	
Weight Height (R)	0 → 1 → 2	0 → 1 → 2	0 → 1 → 2	0 → 1 → 2	0 → 1 → 2	
Weight Width (S)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	
Batch (N)	0		0		0	
Output Channel (K)	0 1		0 1		0 1	
Output Height (Y')	0		1		0	
Output Width (X')	0		0		0	



Data Reuse Analysis

		Cluster 0			Cluster 1		
Input Tensor	PE 0	PE 1	PE 2	PE 3	PE 4	PE 5	
	Batch (N)	0	0	0	0	0	0
	Input Channel (C)	0 1	0 1	0 1	0 1	0 1	0 1
	Input Height (Y)	0	1	2	1	2	3
	Input Width (X)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2

Weight Tensor	Output Channel (K)	0 1	0 1	0 1	0 1	0 1	0 1
	Input Channel (C)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2
	Weight Height (R)	0	1	2	0	1	2
	Weight Width (S)	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2	0 1 2

Output Tensor	Batch (N)	0			0		
	Output Channel (K)	0 1			0 1		
	Output Height (Y')	0			1		
	Output Width (X')	0			0		

