DNN Accelerator Architectures

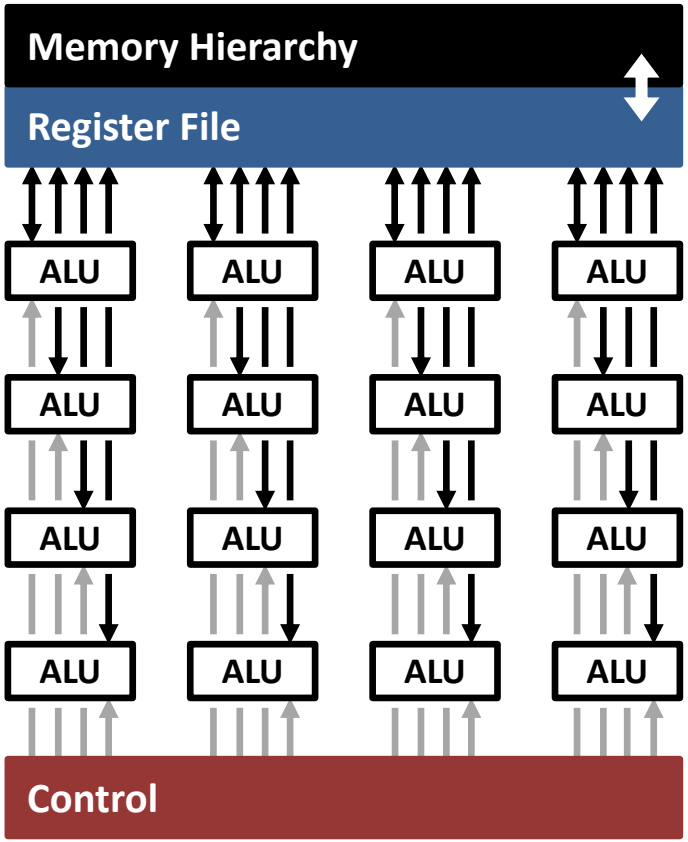
ISCA Tutorial (2019)

Website: http://eyeriss.mit.edu/tutorial.html

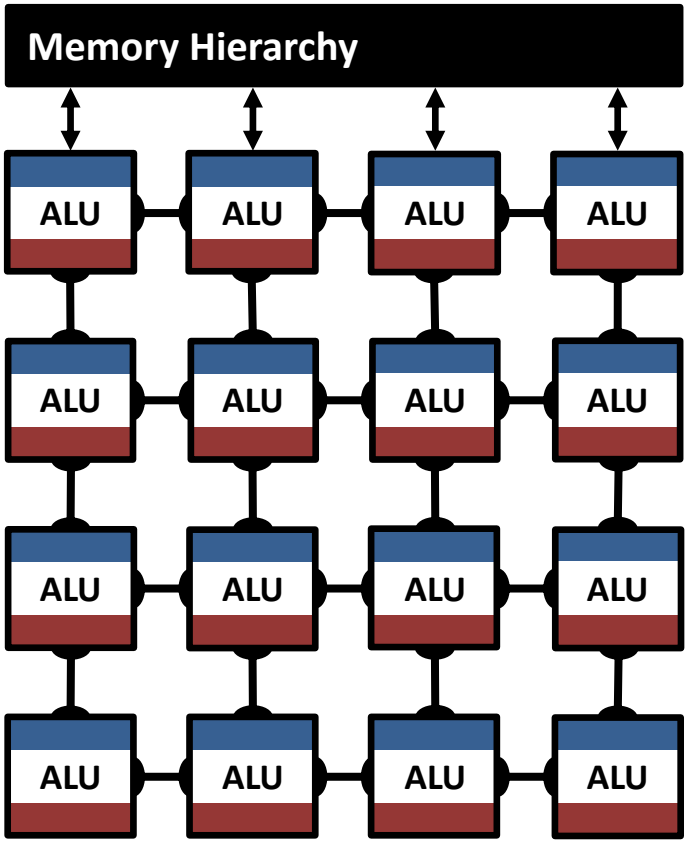
Joel Emer, Vivienne Sze, Yu-Hsin Chen

Highly-Parallel Compute Paradigms

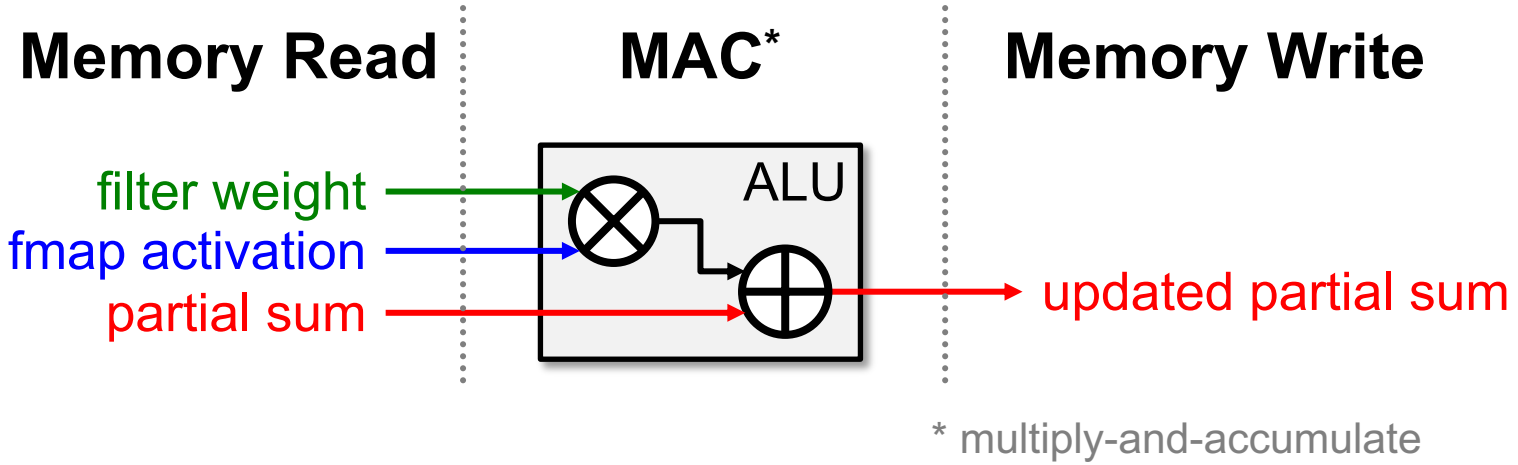
Temporal Architecture (SIMD/SIMT)



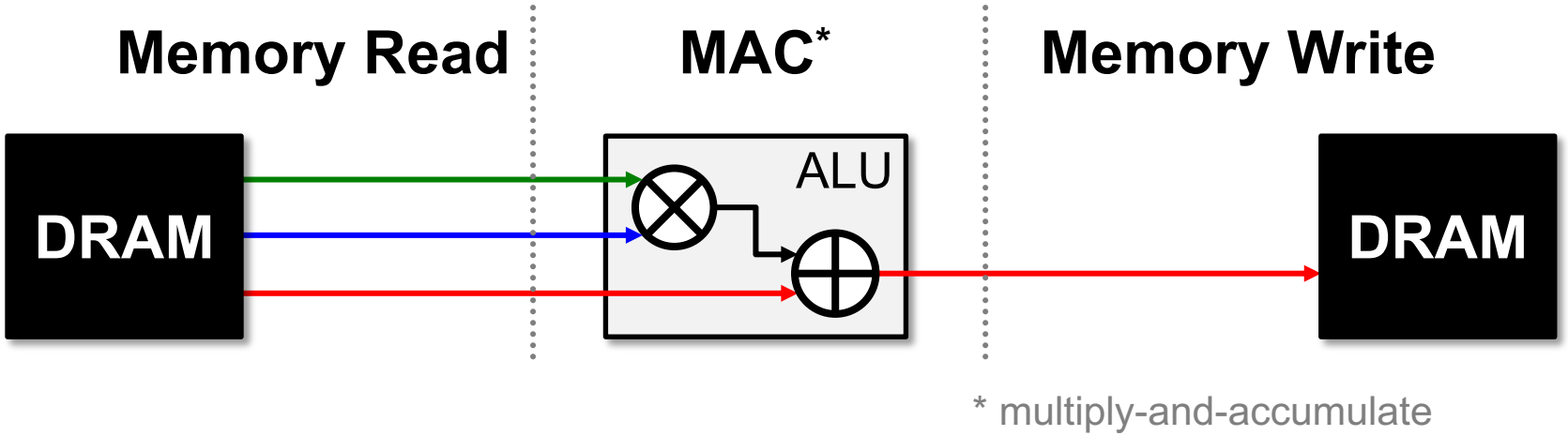
Spatial Architecture (Dataflow Processing)



Memory Access is the Bottleneck



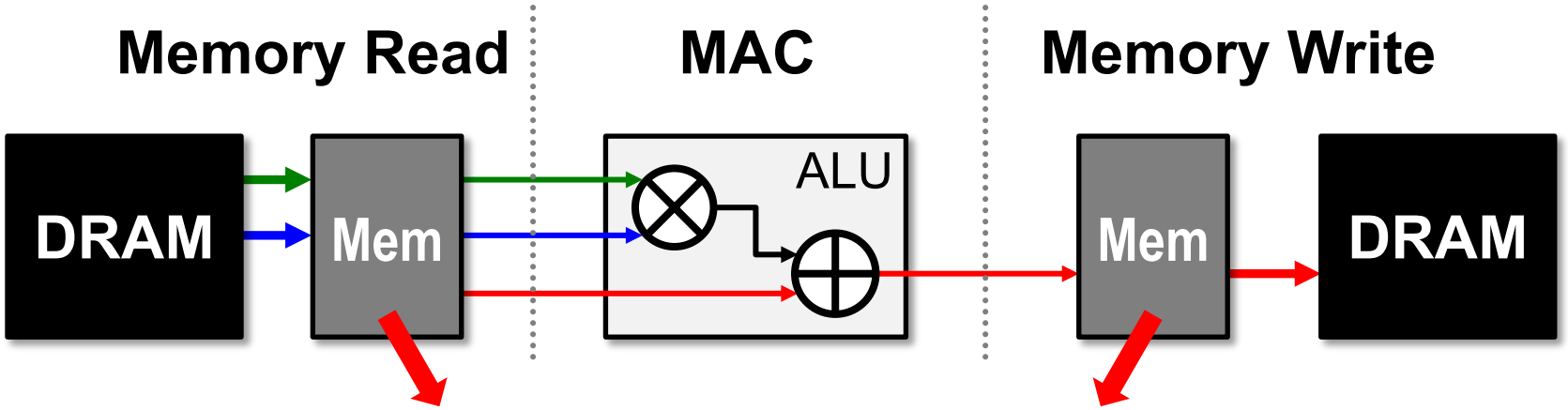
Memory Access is the Bottleneck



Worst Case: all memory R/W are **DRAM** accesses

- Example: AlexNet [NIPS 2012] has **724M** MACs
  → **2896M** DRAM accesses required

Leverage Local Memory for Data Reuse



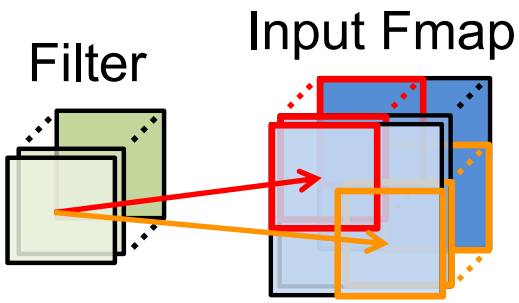
Extra levels of local memory hierarchy

Smaller, but **Faster** and **more Energy-Efficient**

Types of Data Reuse in DNN

Convolutional Reuse

CONV layers only
(sliding window)

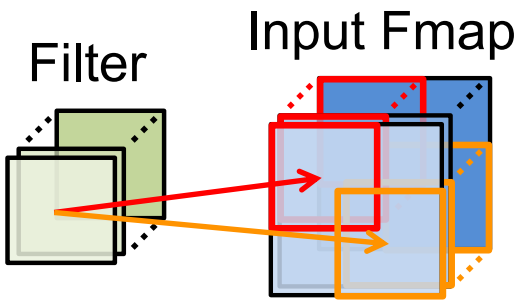


Reuse: Activations
Filter weights

Types of Data Reuse in DNN

Convolutional Reuse

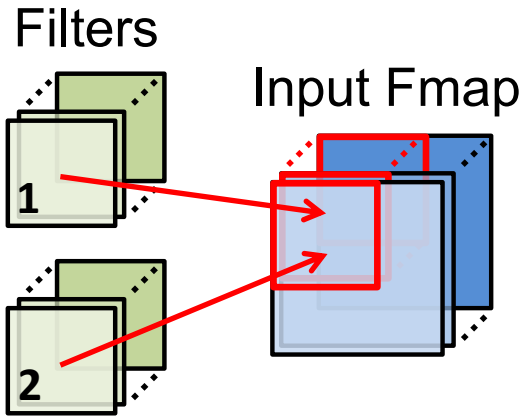
CONV layers only
(sliding window)



Reuse: Activations
Filter weights

Fmap Reuse

CONV and FC layers

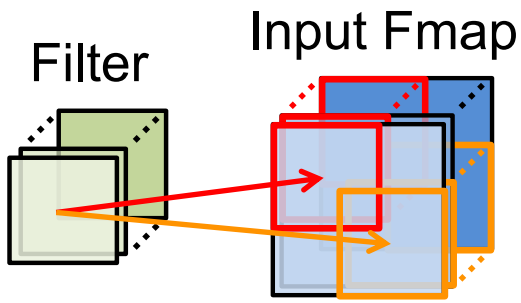


Reuse: Activations

Types of Data Reuse in DNN

Convolutional Reuse

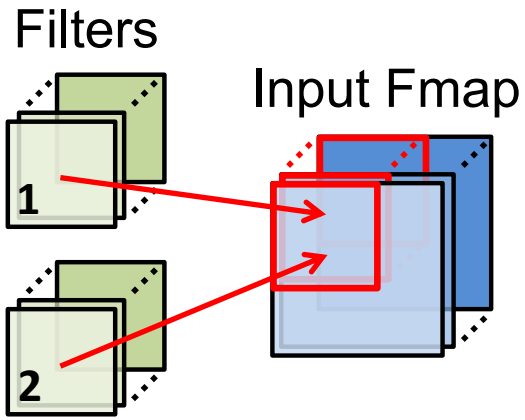
CONV layers only
(sliding window)



Reuse: Activations
Filter weights

Fmap Reuse

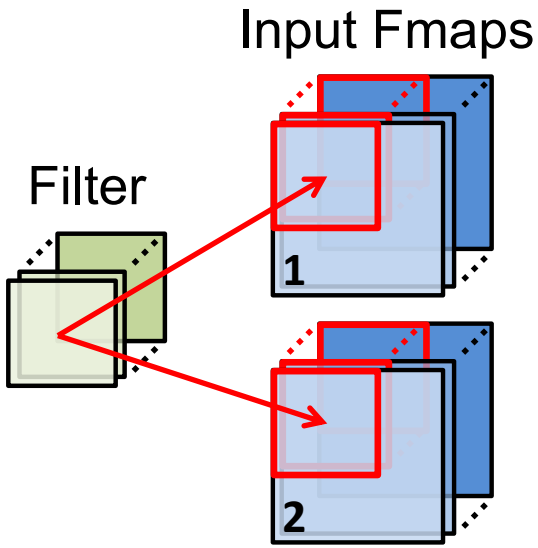
CONV and FC layers



Reuse: Activations

Filter Reuse

CONV and FC layers
(batch size > 1)



Reuse: Filter weights

Types of Data Reuse in DNN

Convolutional Reuse

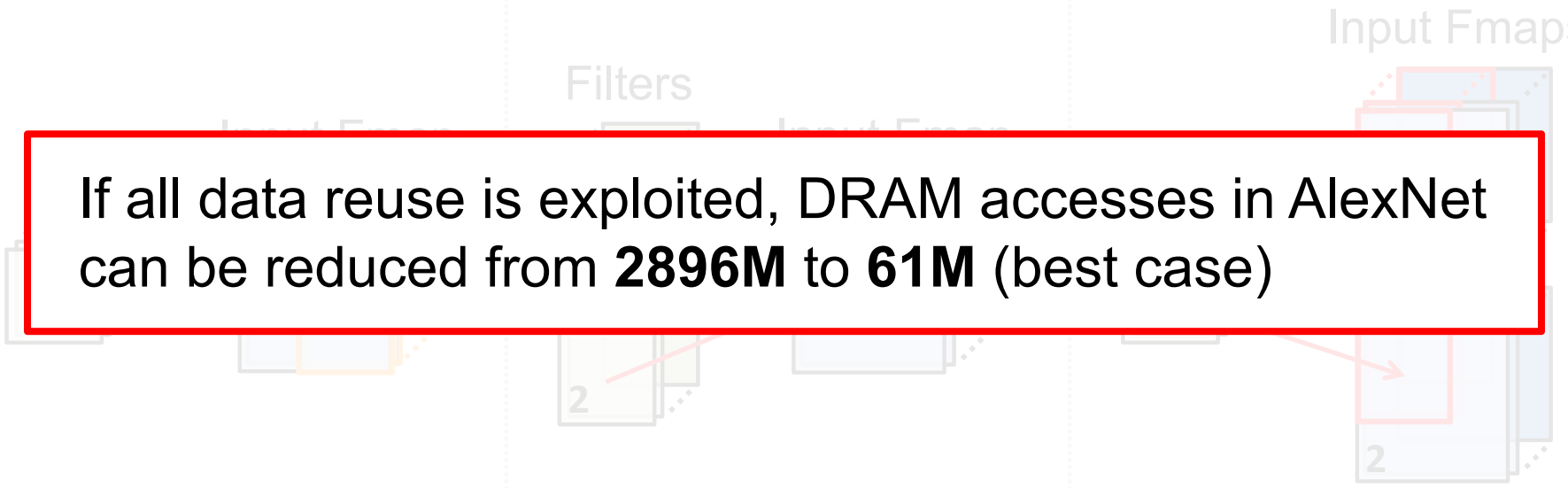
CONV layers only (sliding window)

Fmap Reuse

CONV and FC layers

Filter Reuse

CONV and FC layers (batch size > 1)



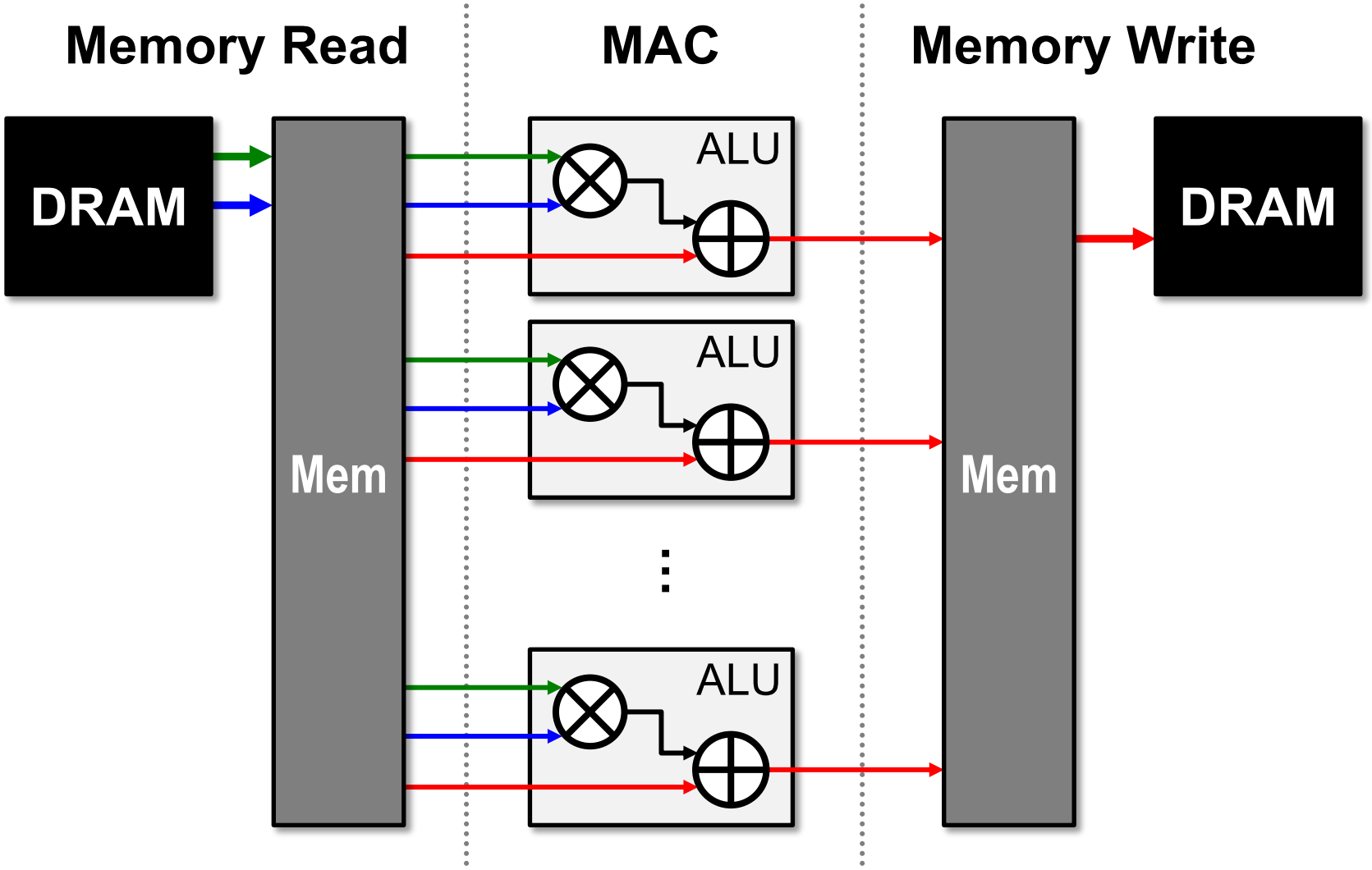
If all data reuse is exploited, DRAM accesses in AlexNet can be reduced from **2896M** to **61M** (best case)

Reuse: Activations, Filter weights

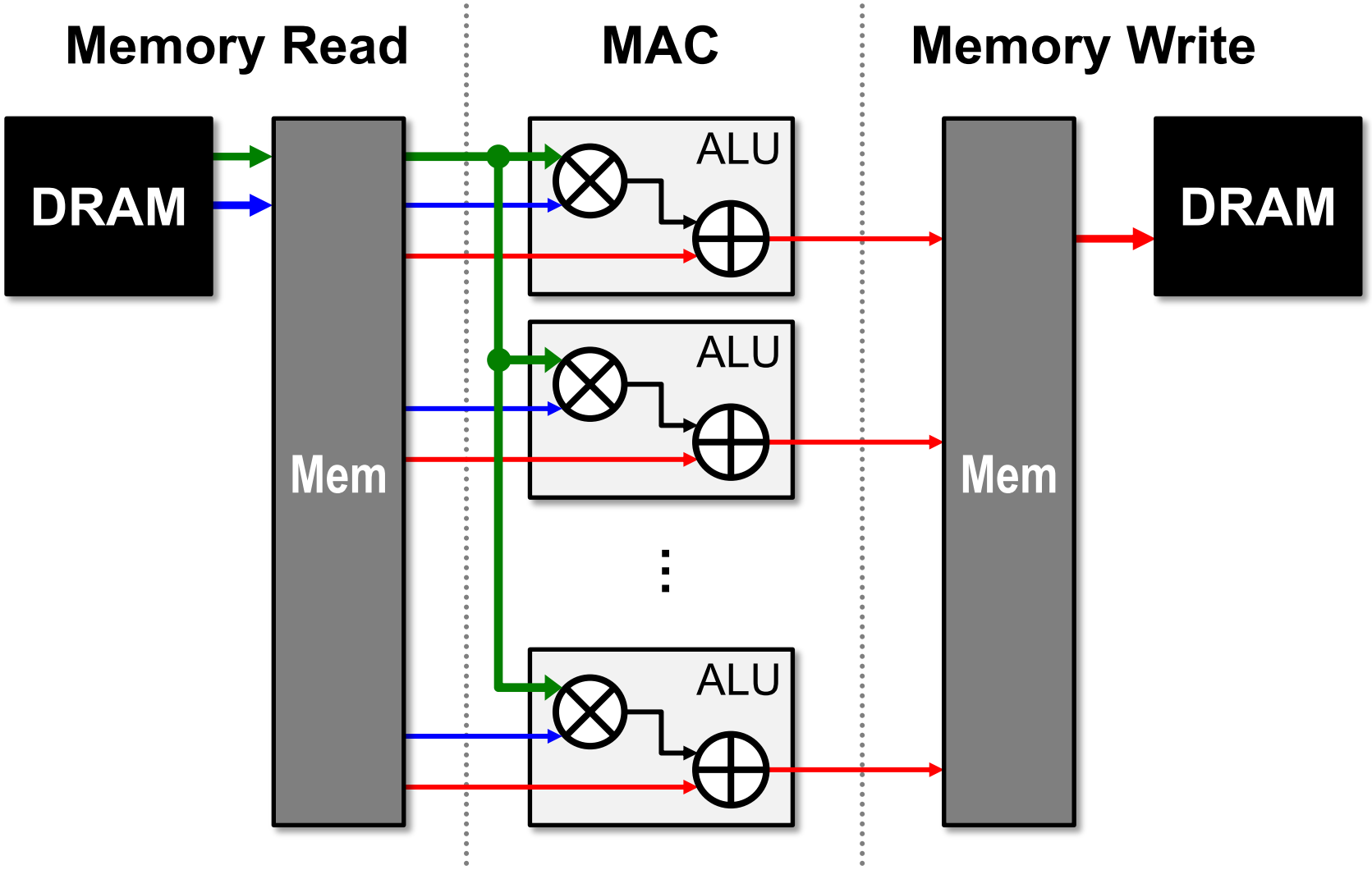
Reuse: Activations

Reuse: Filter weights

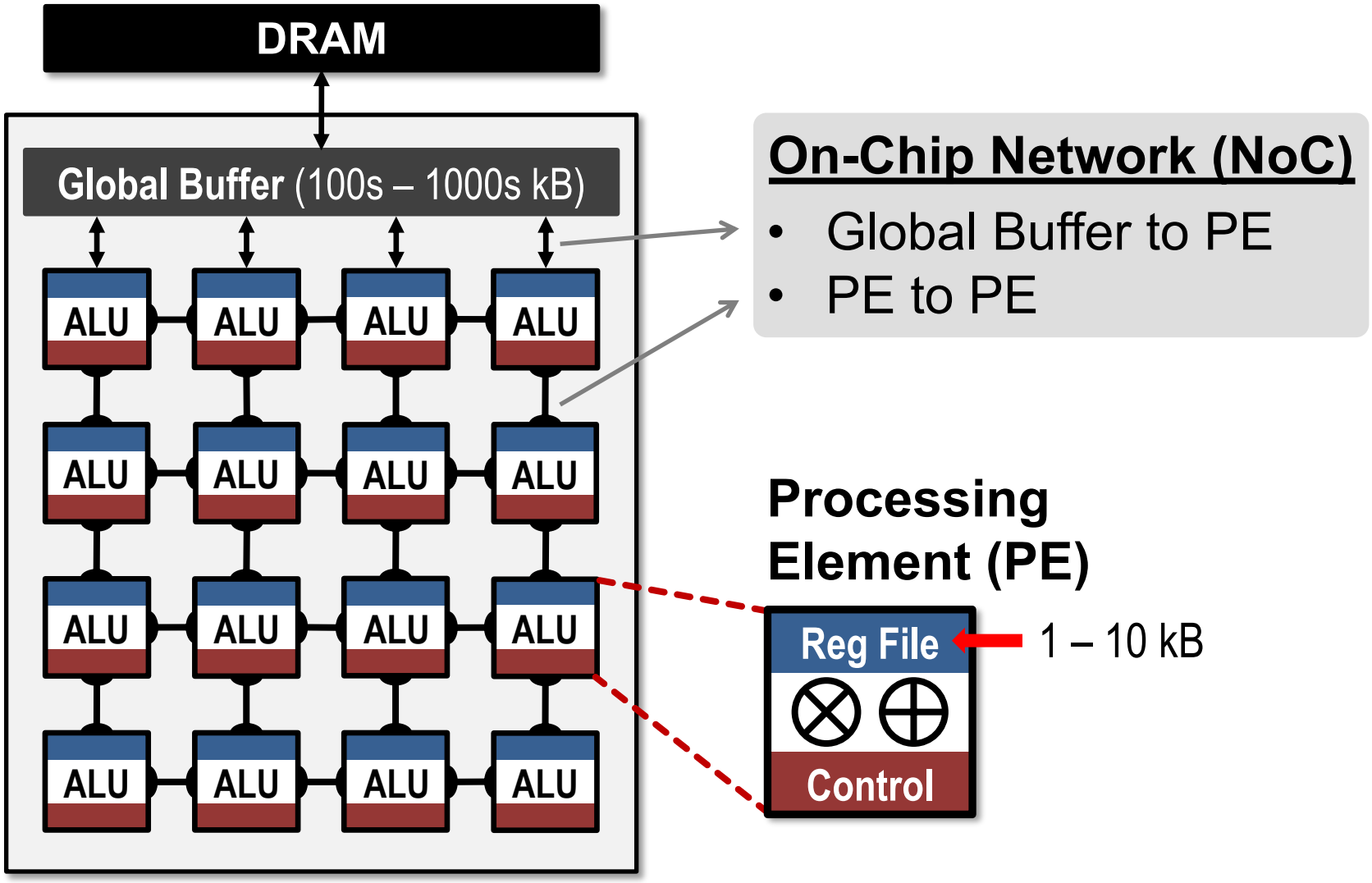
Leverage Parallelism for Higher Performance



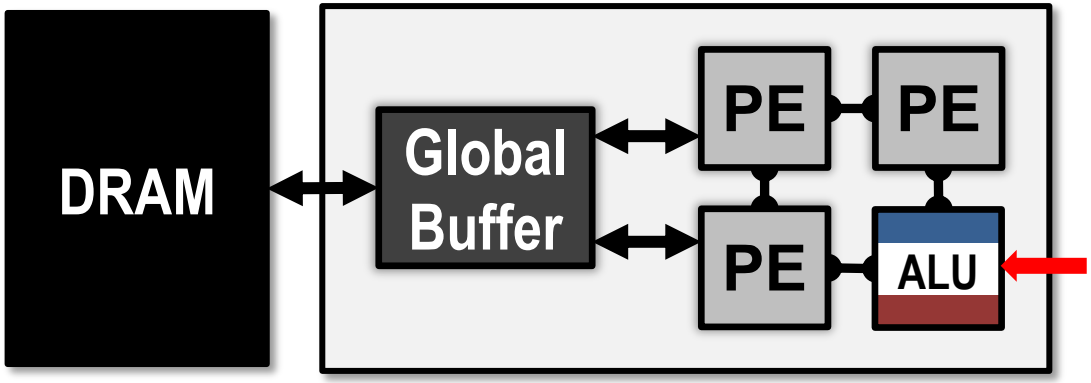
Leverage Parallelism for *Spatial* Data Reuse

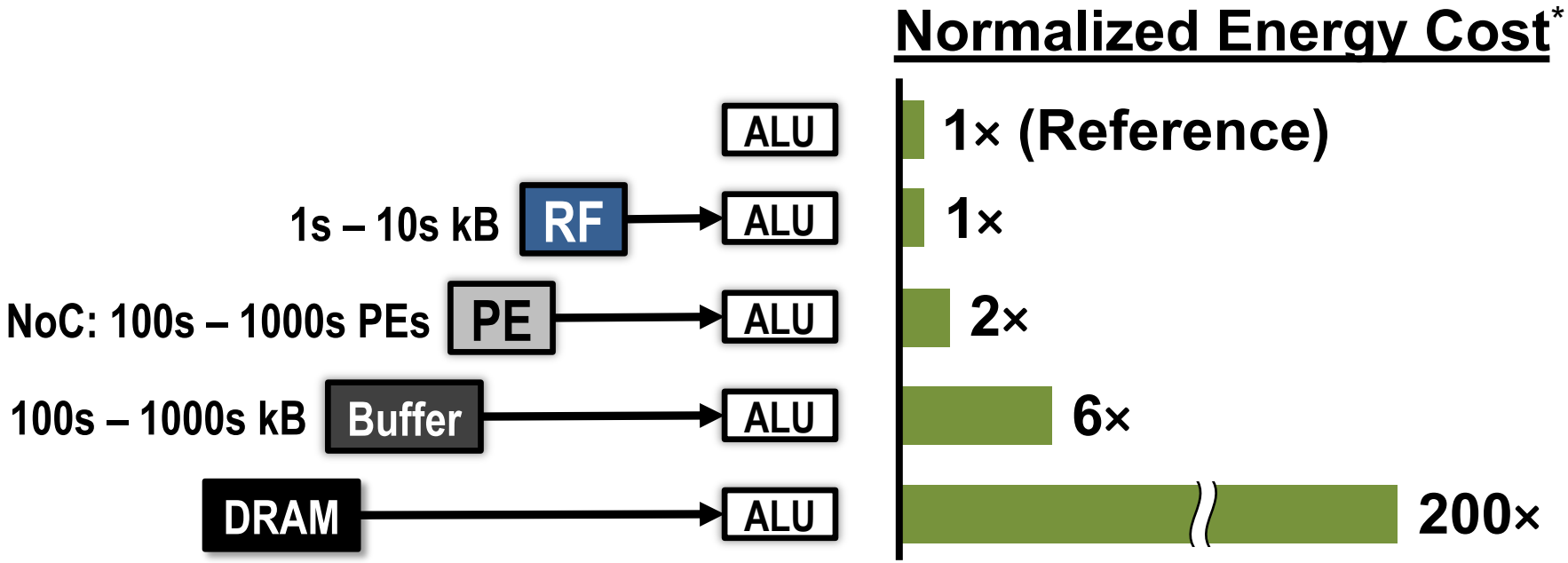


Spatial Architecture for DNN



Multi-Level Low-Cost Data Access

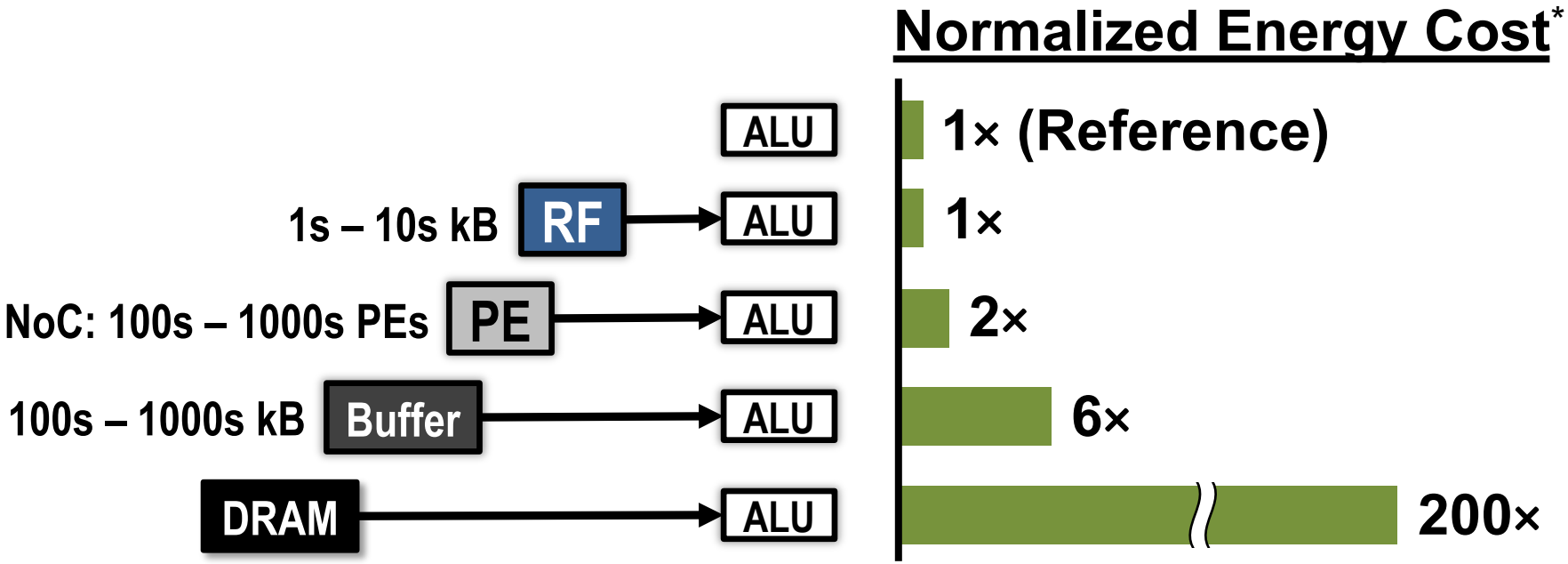




* measured from a commercial 65nm process

Multi-Level Low-Cost Data Access

A **Dataflow** is required to maximally exploit **data reuse** with the **low-cost memory hierarchy** and **parallelism**



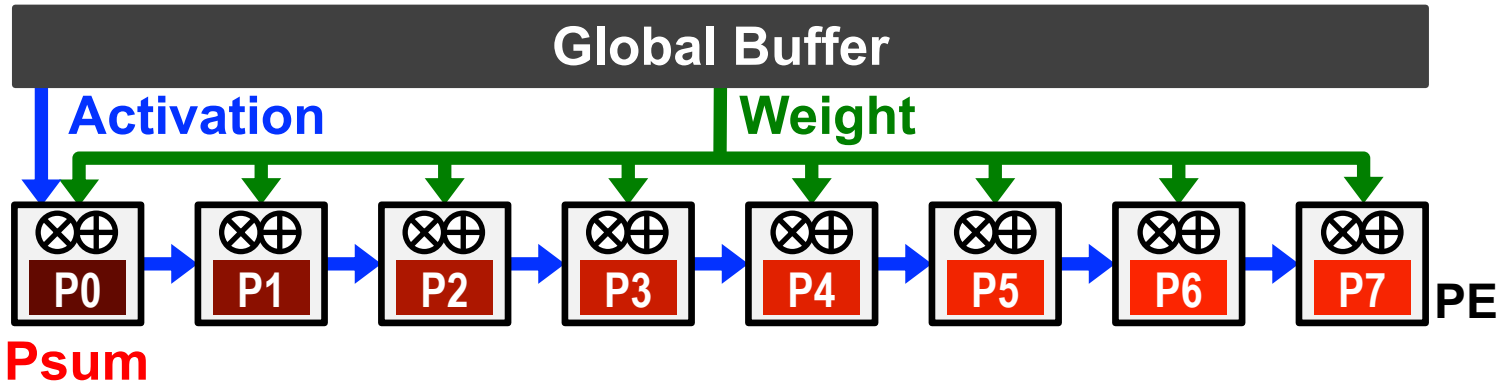
* measured from a commercial 65nm process

Dataflow Taxonomy

- Output Stationary (OS)
- Weight Stationary (WS)
- Input Stationary (IS)

[Chen et al., ISCA 2016]

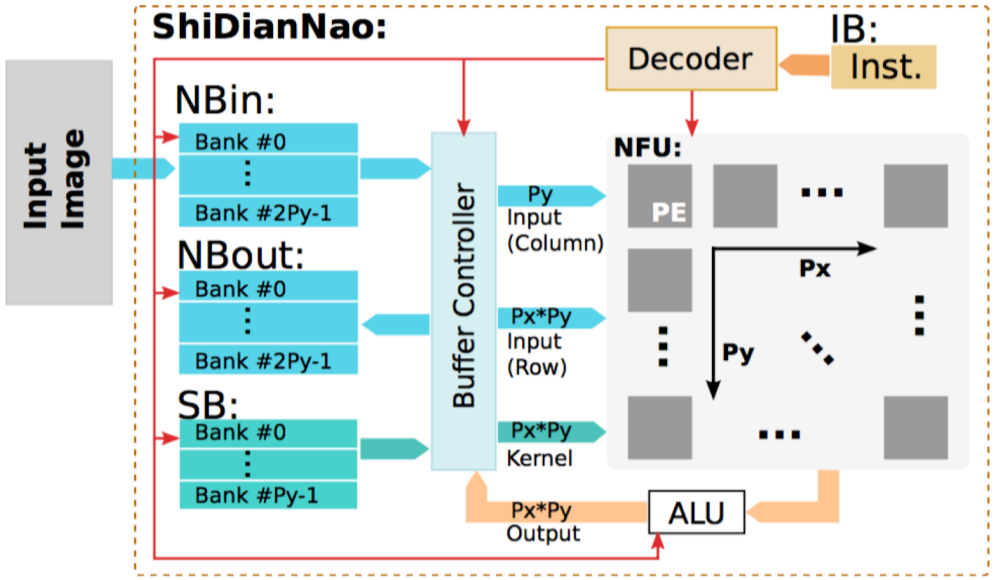
Output Stationary (OS)



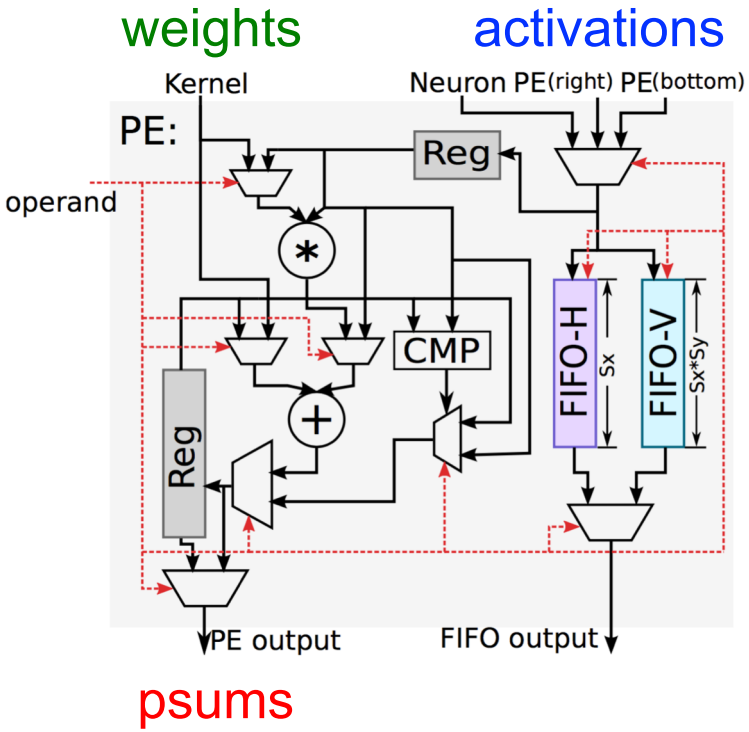
- **Minimize partial sum** R/W energy consumption
  - maximize local accumulation
- **Broadcast/Multicast filter weights** and **reuse activations spatially** across the PE array

OS Example: ShiDianNao

Top-Level Architecture

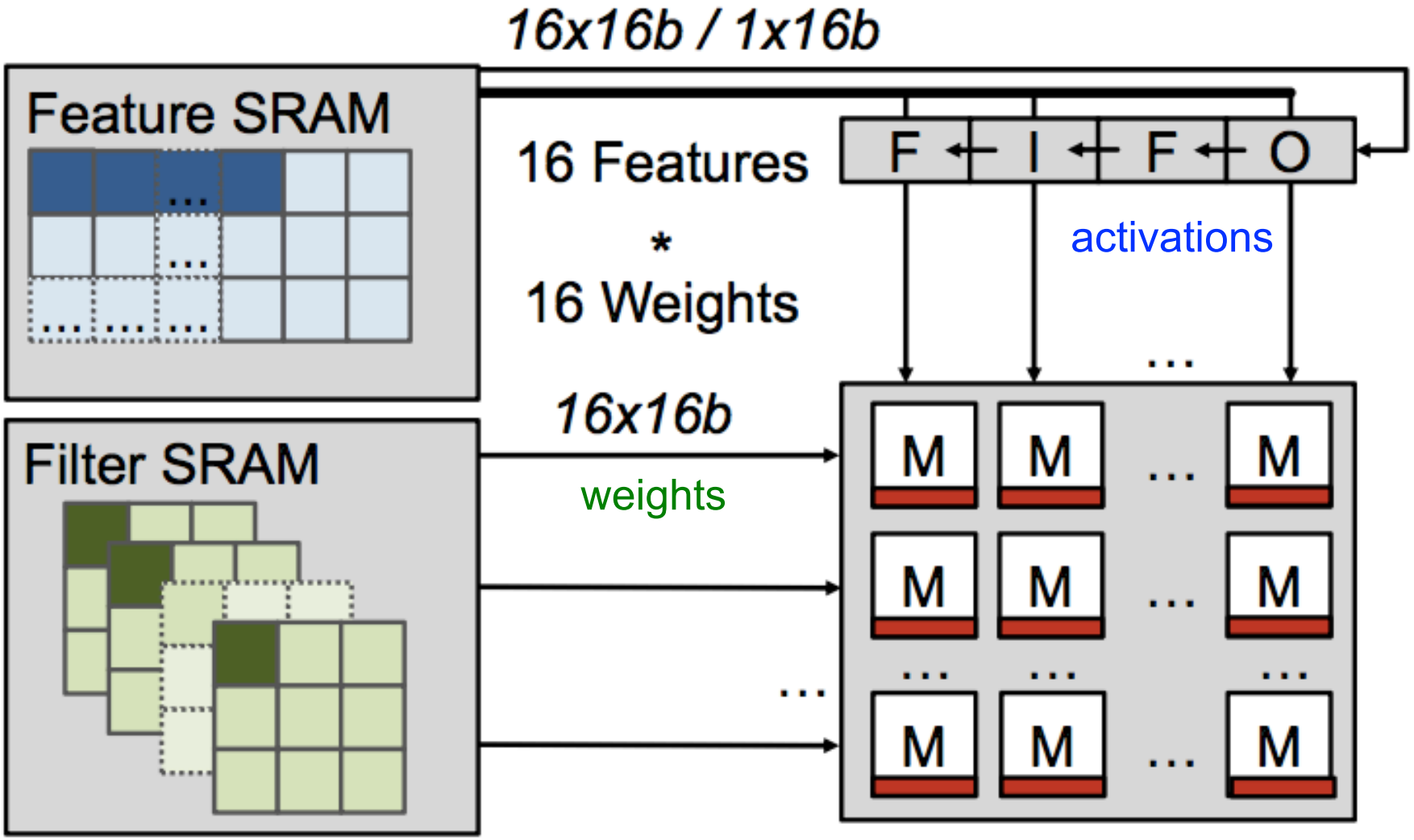


PE Architecture



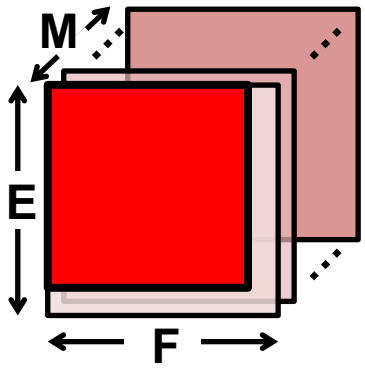
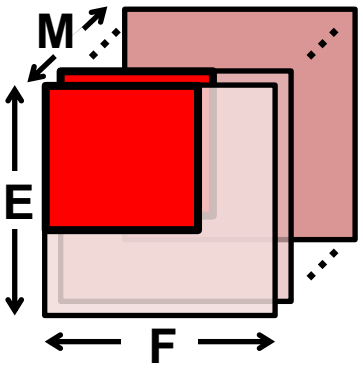
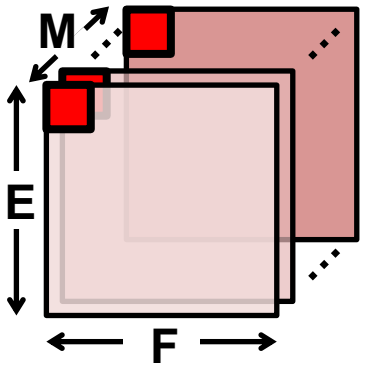
[Du et al., ISCA 2015]

OS Example: ENVISION

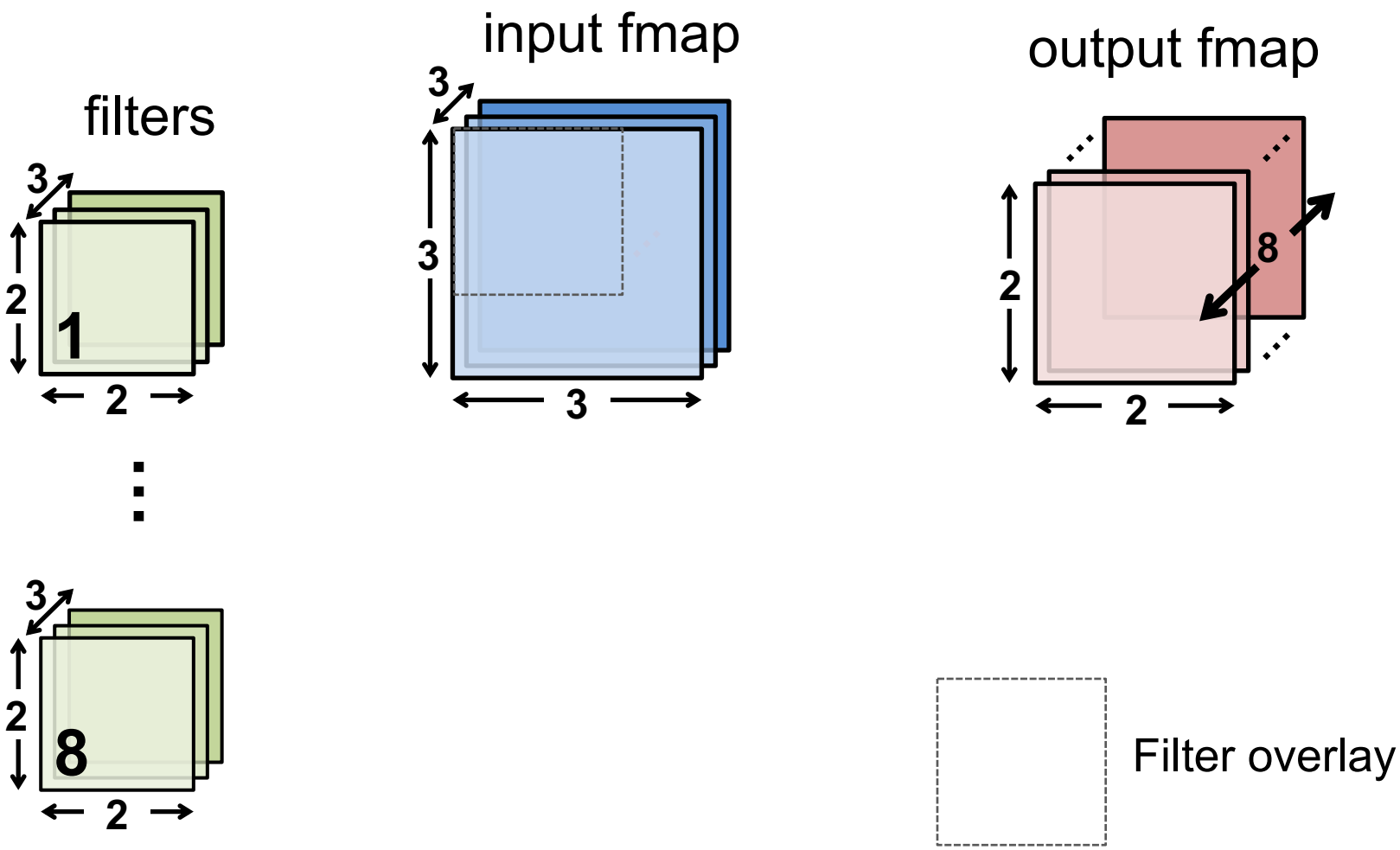


[Moons et al., VLSI 2016, ISSCC 2017]

Variants of Output Stationary

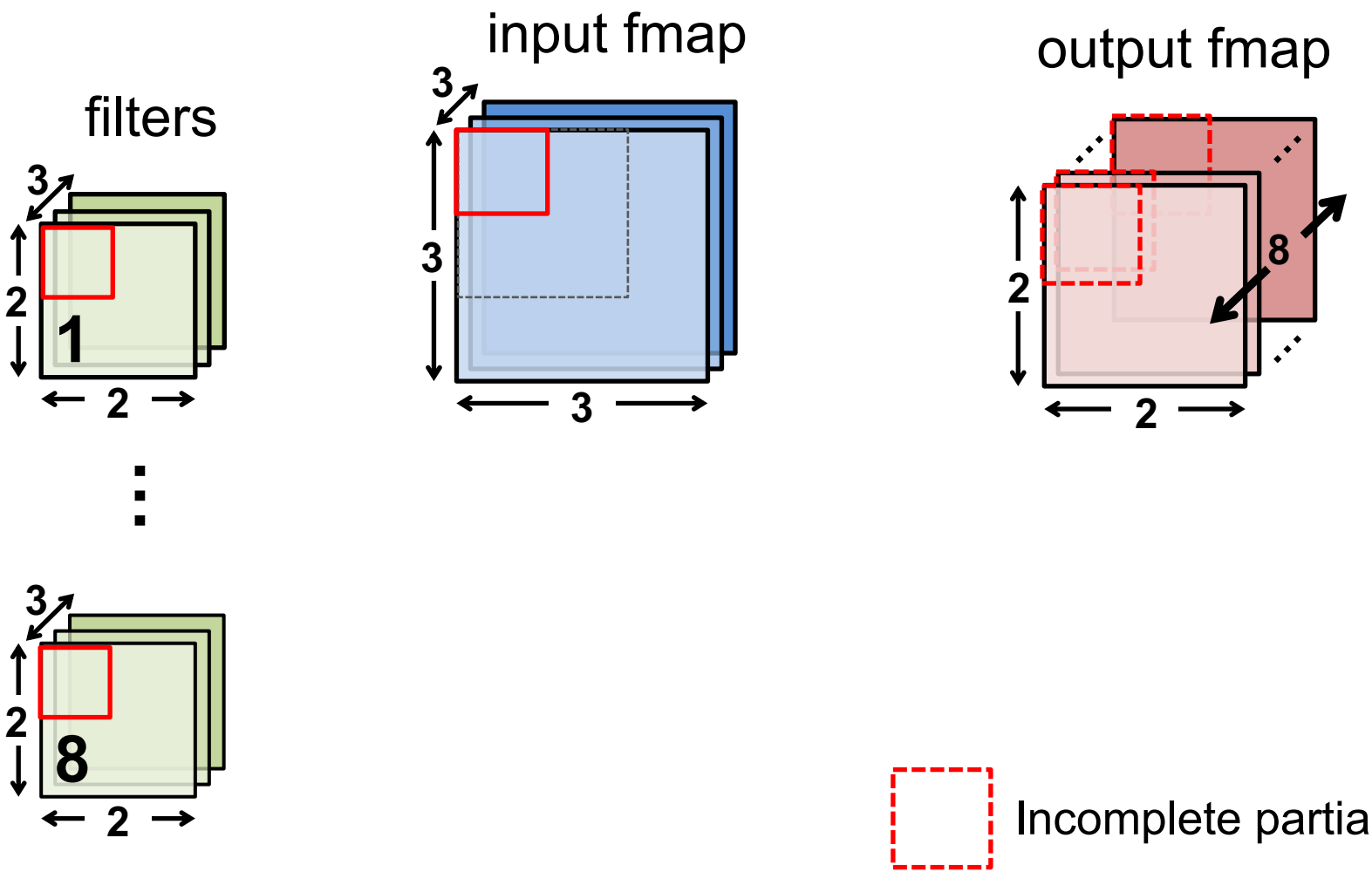
	OS_A	OS_B	OS_C
Parallel Output Region			
# Output Channels	Single	Multiple	Multiple
# Output Activations	Multiple	Multiple	Single
Notes	Targeting **CONV** layers		Targeting **FC** layers

OS Example


filters
3
2
1
2
3
2
8
2
input fmap
3
3
3
output fmap
2
8
2
Filter overlay

OS Example

Cycle through input fmap and weights (hold psum of output fmap)



OS Example

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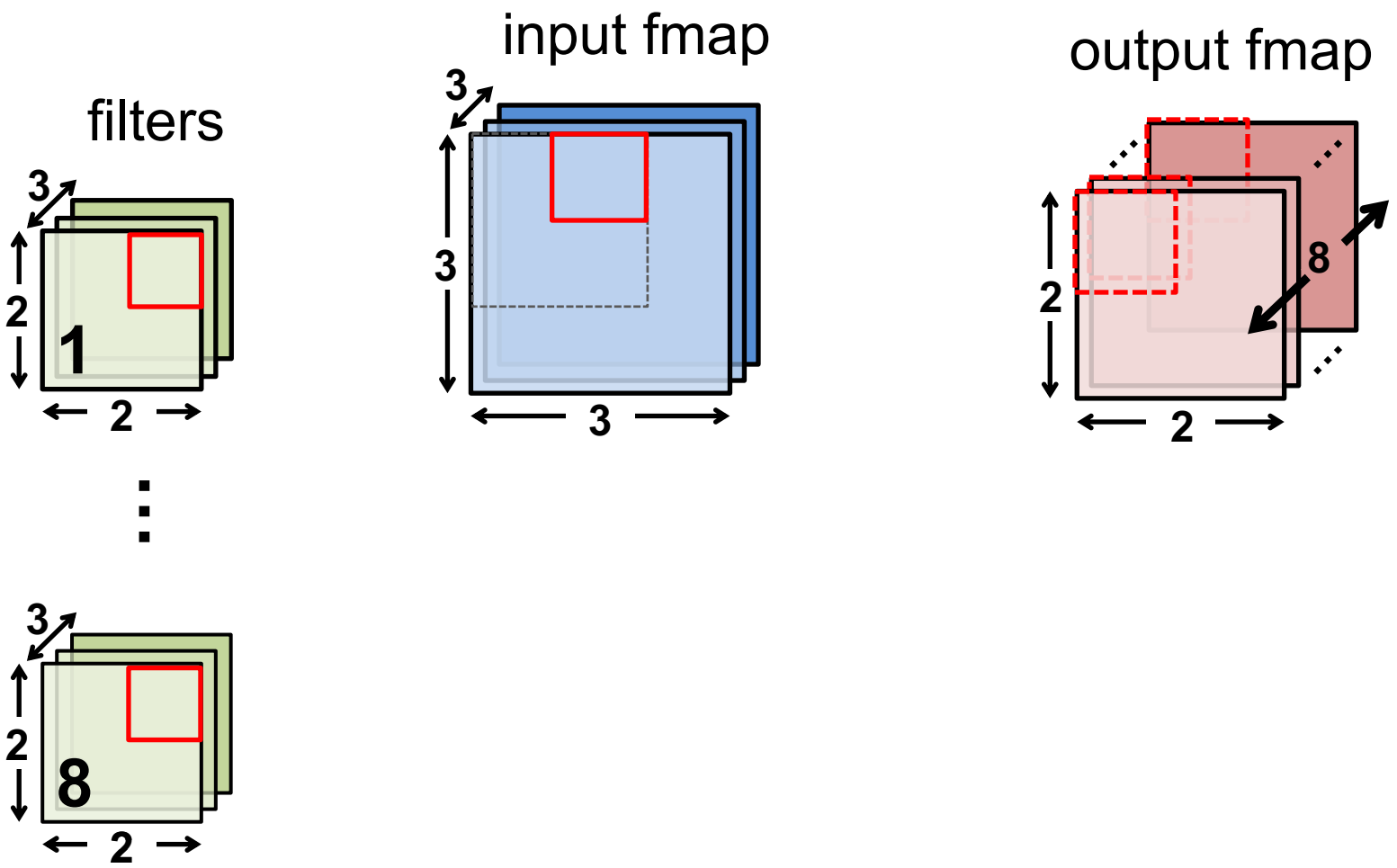
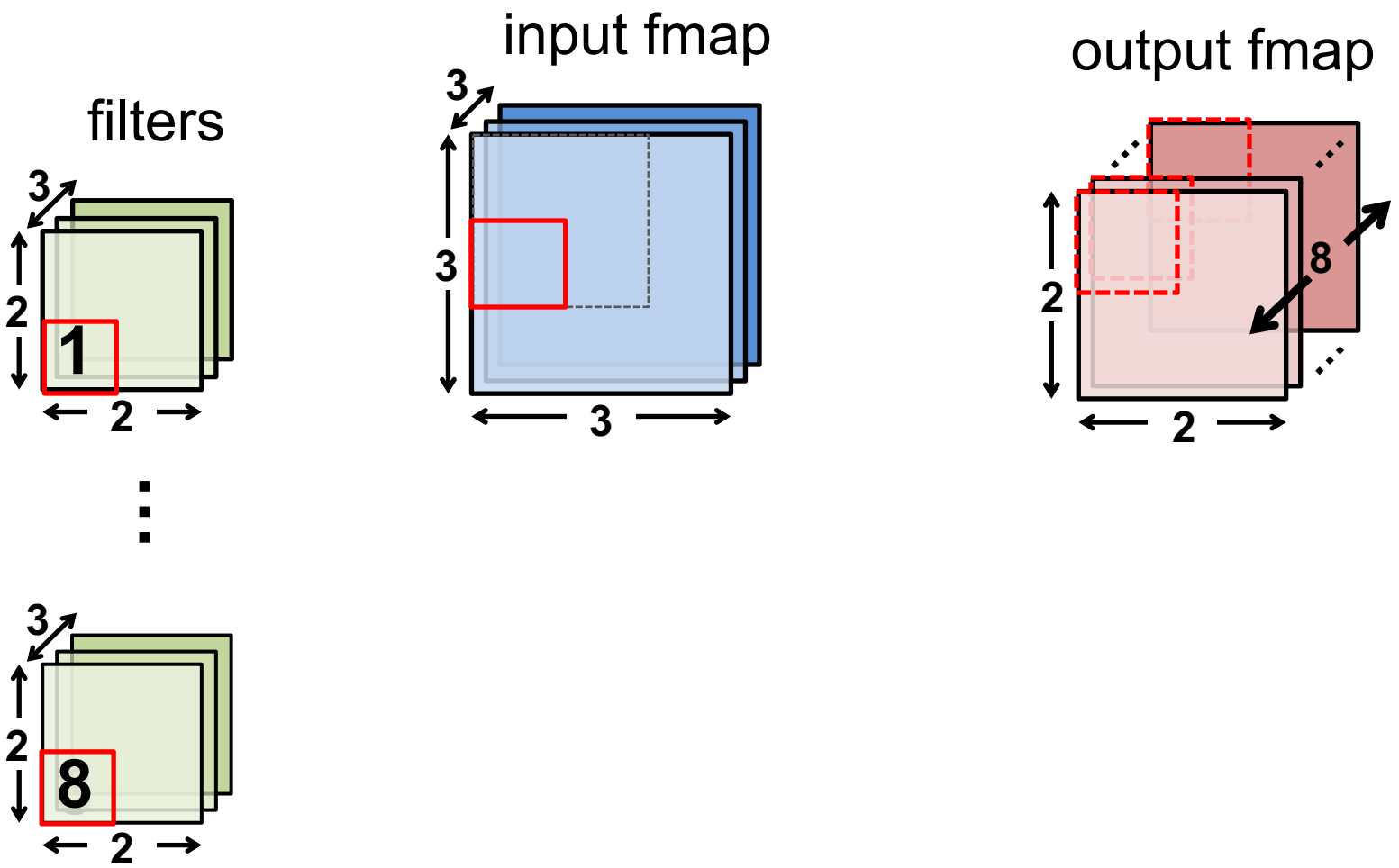


OS Example

Cycle through input fmap and weights (hold psum of output fmap)



OS Example

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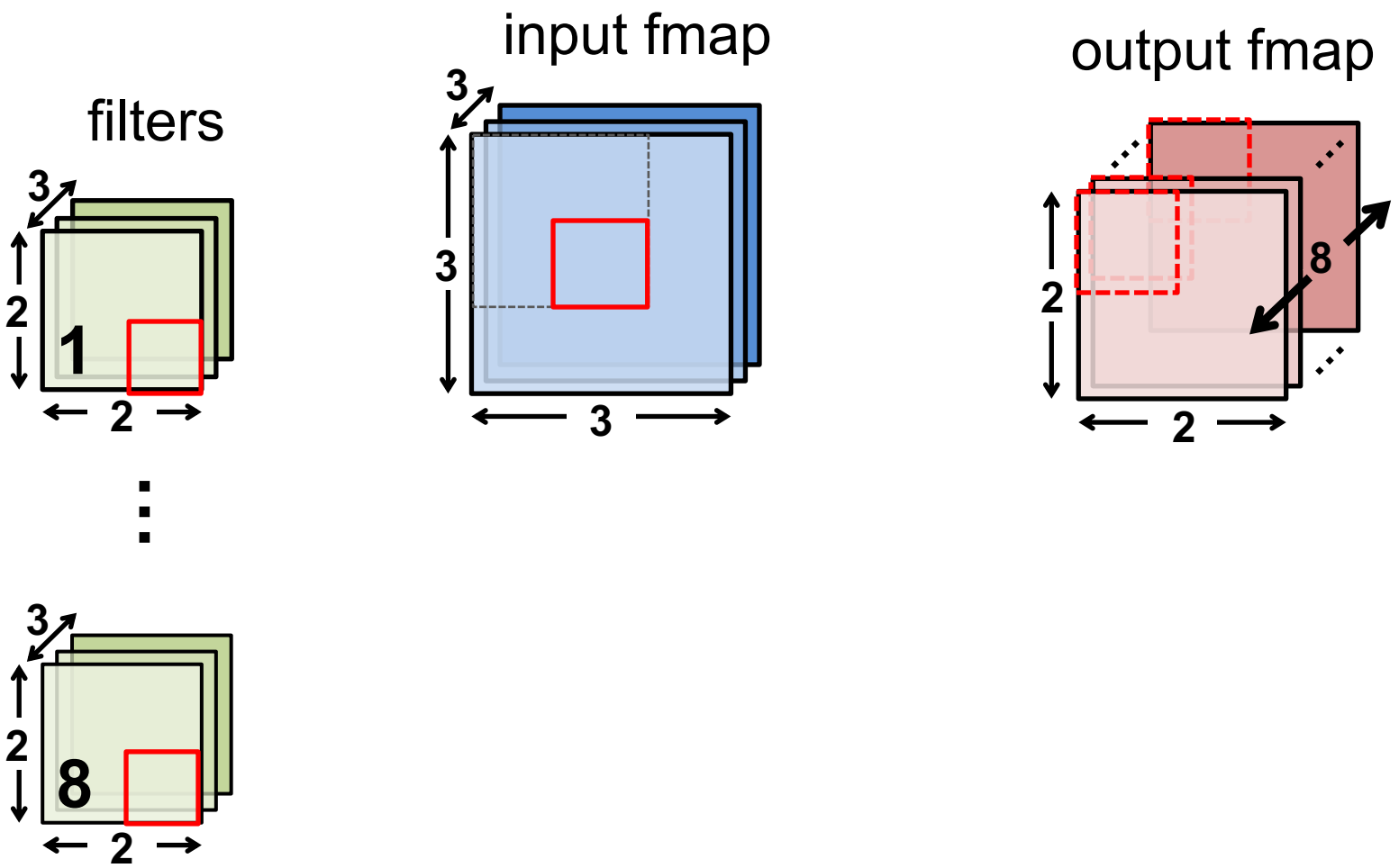

OS Example

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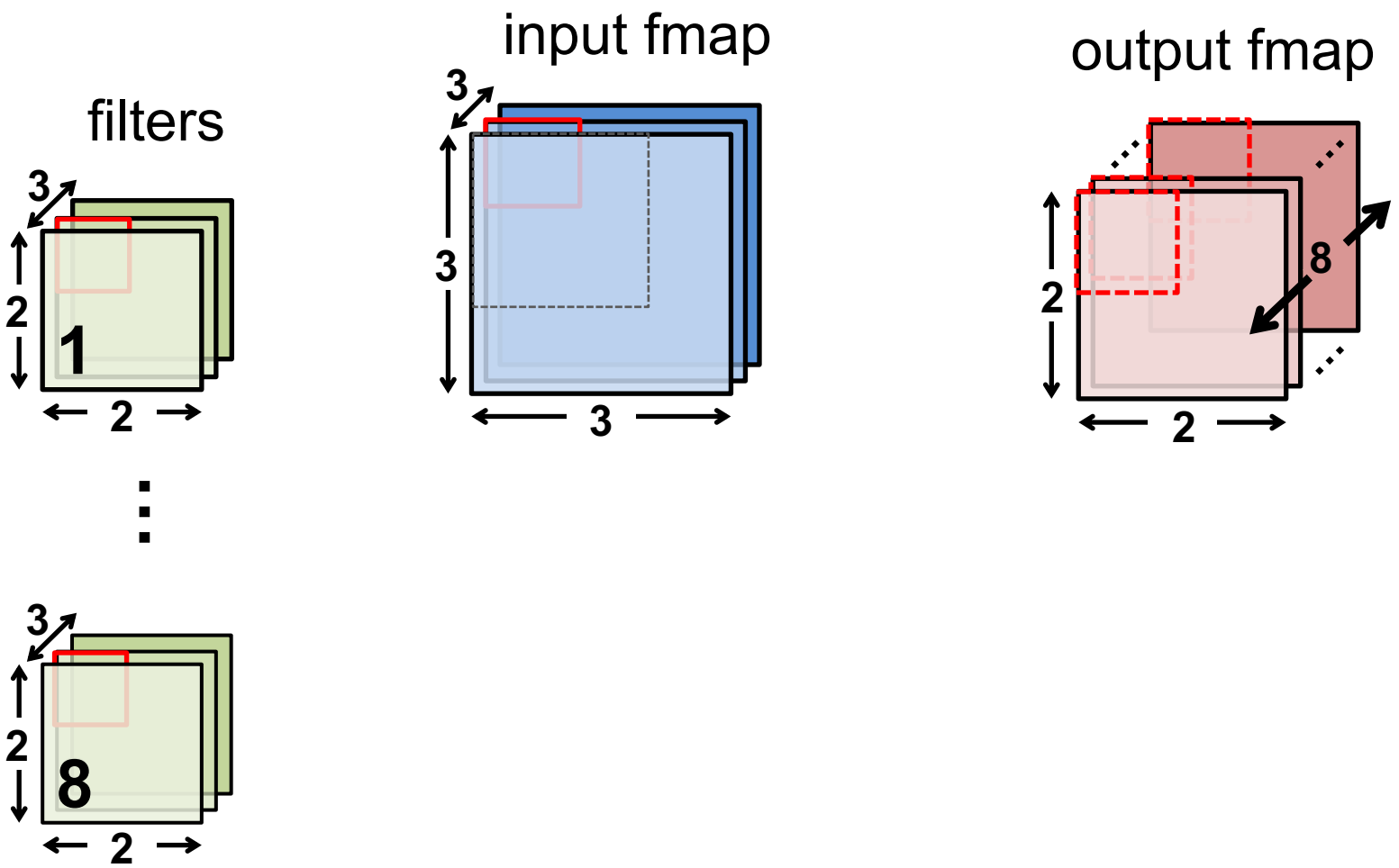
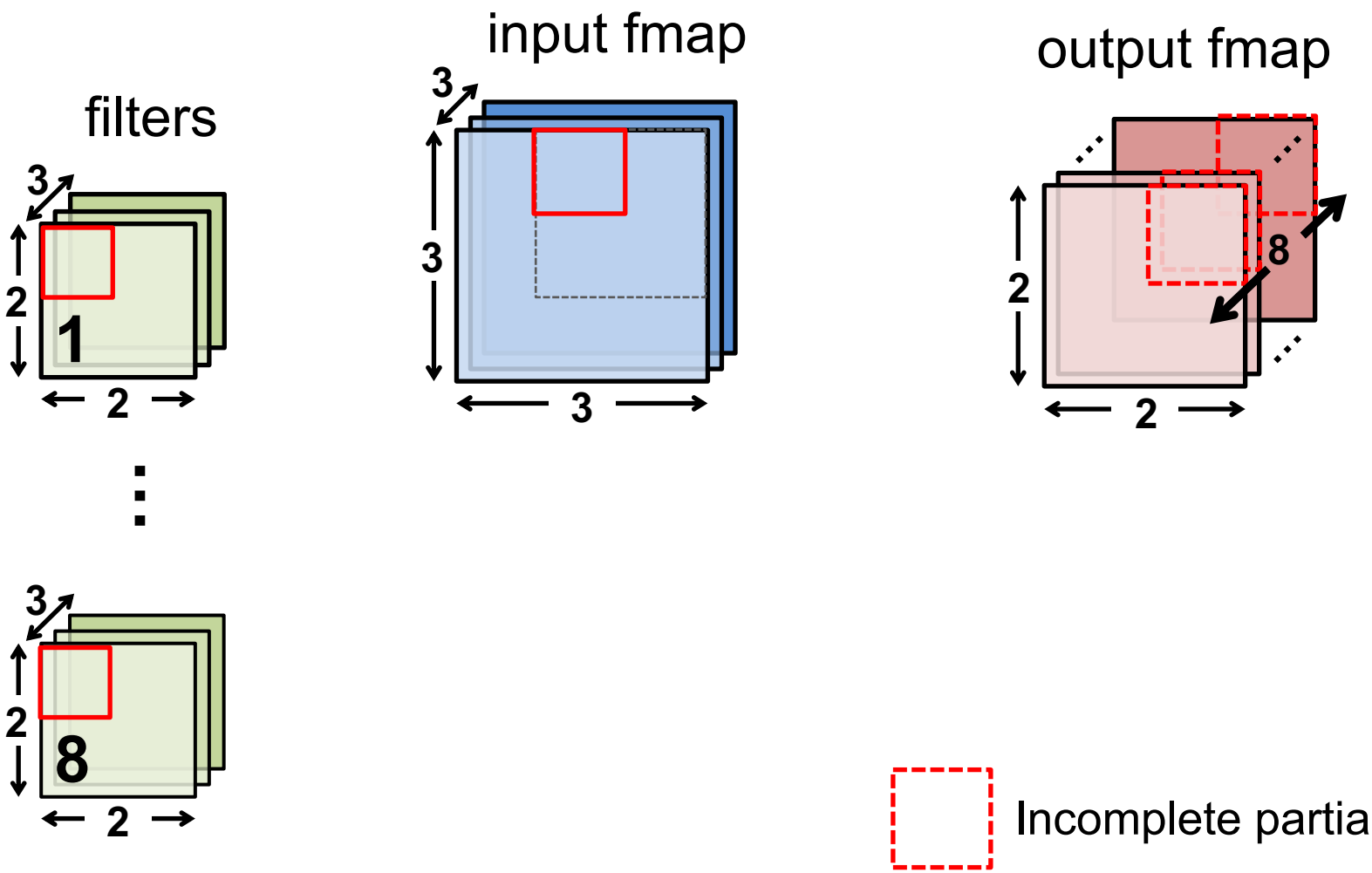


OS Example

Cycle through input fmap and weights (hold psum of output fmap)



1-D Convolution – Output Stationary


```
int I[H];      // Input activations
int W[R];      // Filter weights
int O[E];      // Output activations

for (e = 0; e < E; e++)
    for (r = 0; r < R; r ++)
        O[e] += I[e+r] * W[r];
```

No constraints on loop permutations!

† Assuming: 'valid' style convolution

1-D Convolution


```
int I[H];      // Input activations
int W[R];      // Filter weights
int O[E];      // Output activations

for (r = 0; r < R; r++)
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        O[e] += I[e+r] * W[r];
```
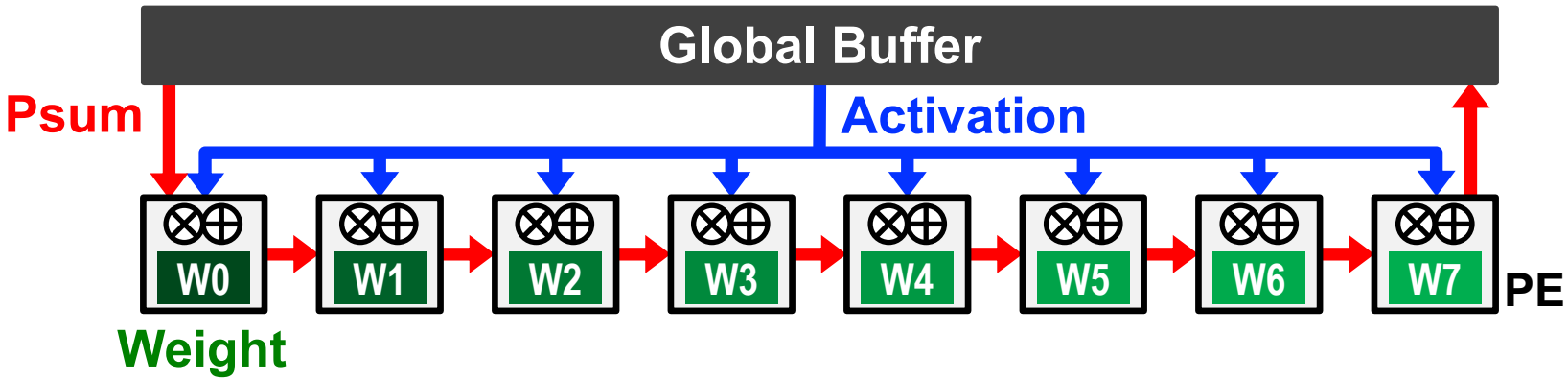

† Assuming: 'valid' style convolution

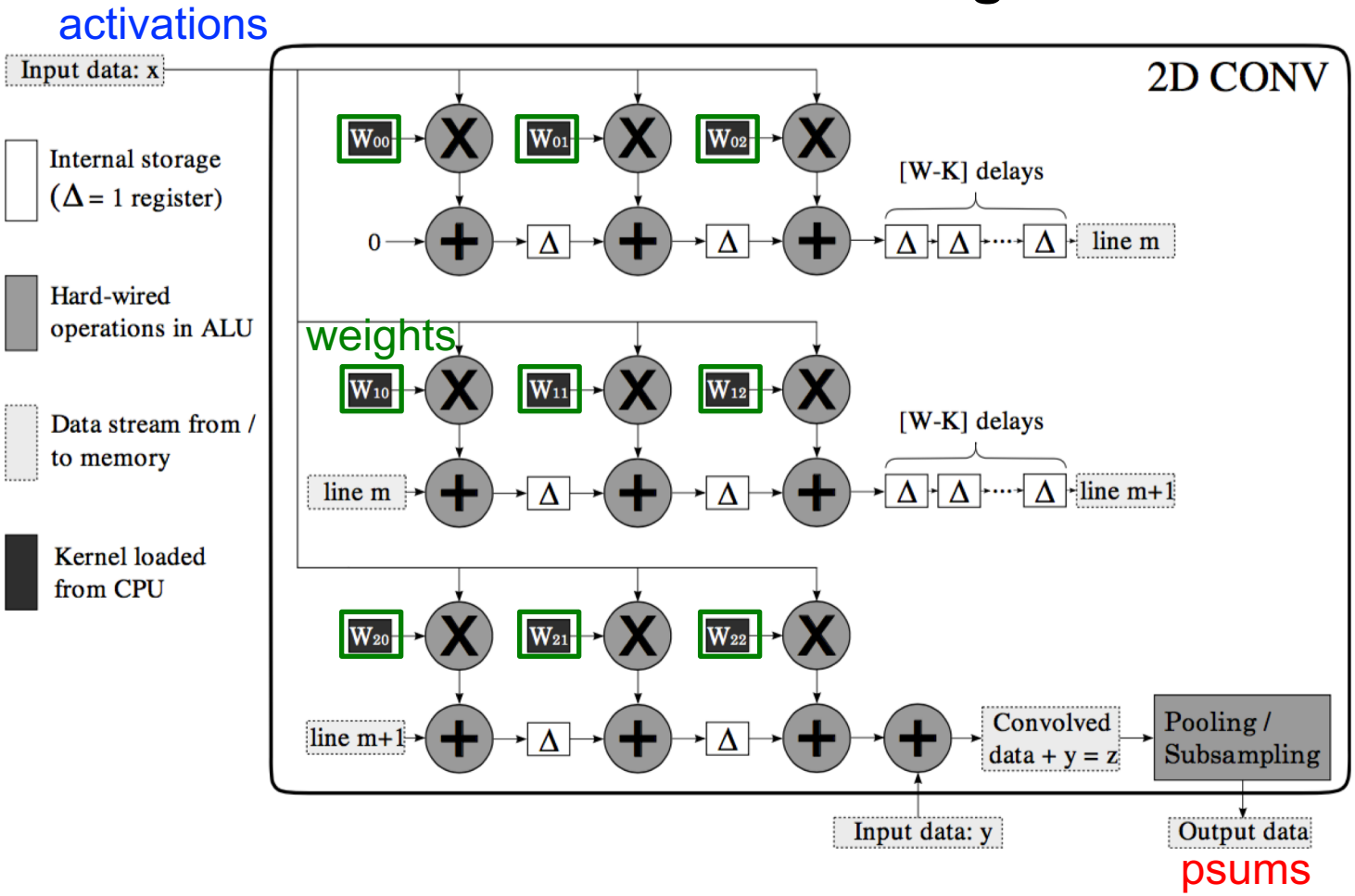
Weight Stationary (WS)



- **Minimize weight** read energy consumption
  - maximize convolutional and filter reuse of weights
- **Broadcast activations** and **accumulate psums spatially** across the PE array.

WS Example: nn-X (NeuFlow)

A 3×3 2D Convolution Engine

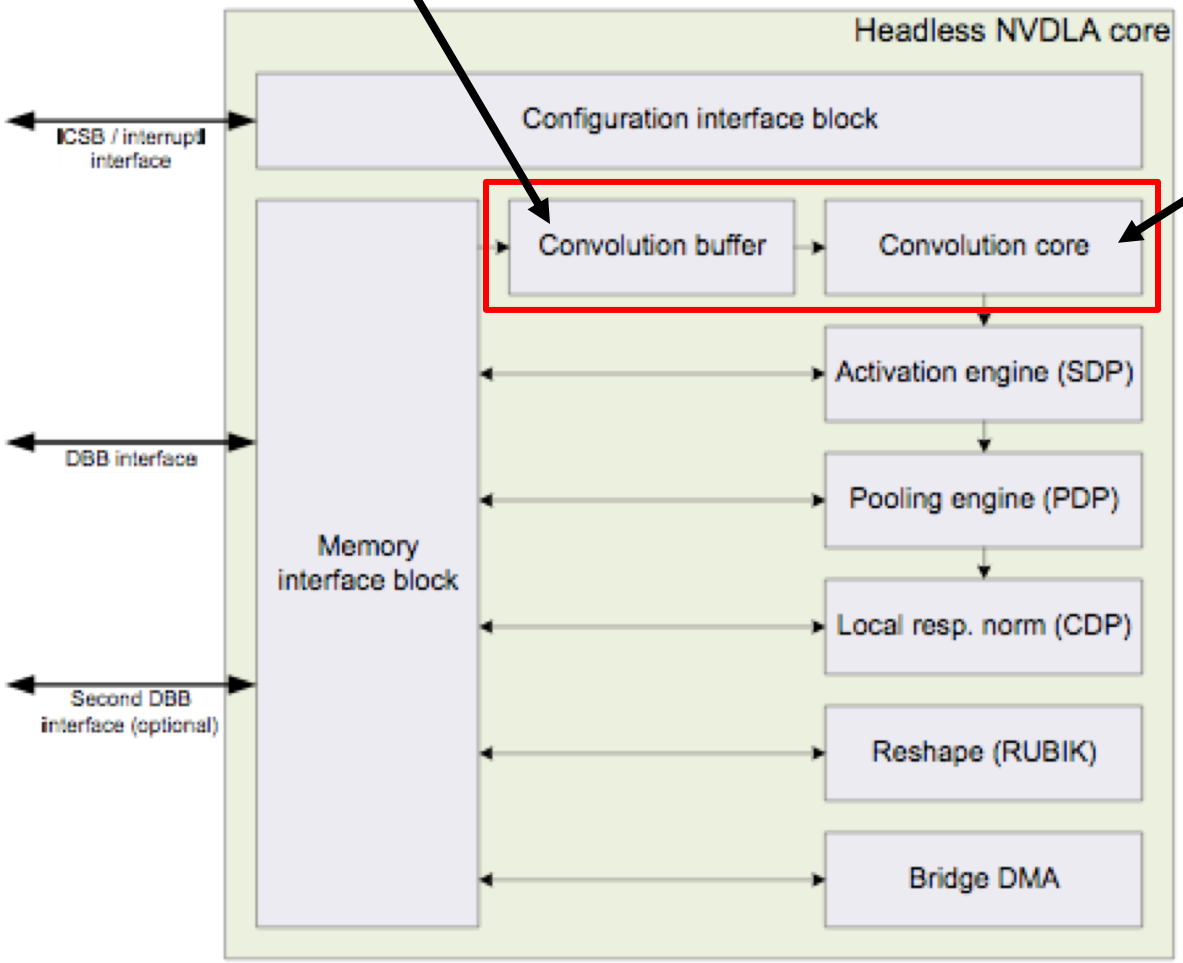


[Farabet et al., ICCV 2009]

WS Example: NVDLA (simplified)

Global Buffer

Released Sept 29, 2017

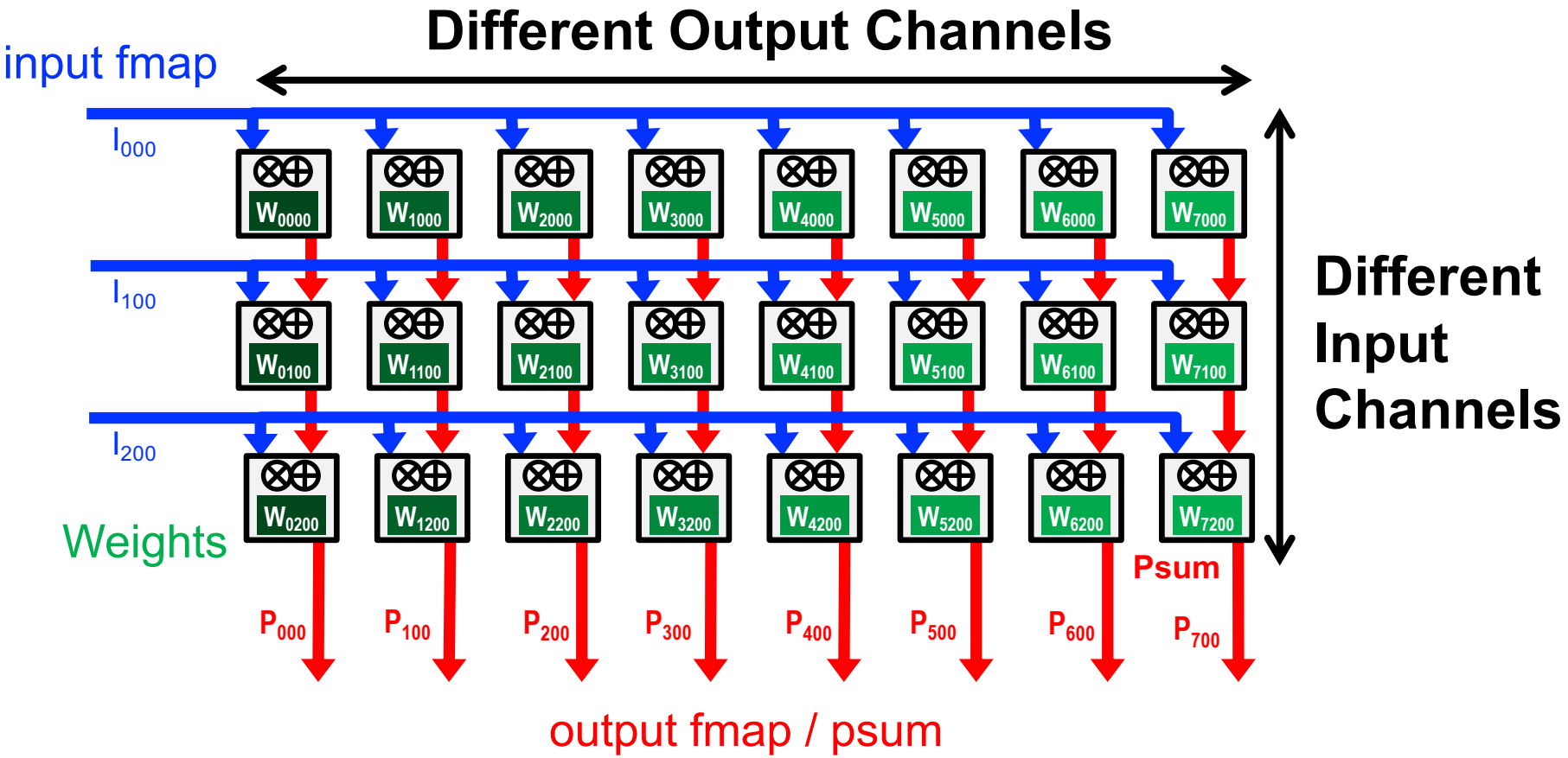


PE Array: *M x C MACs*

Image Source: Nvidia

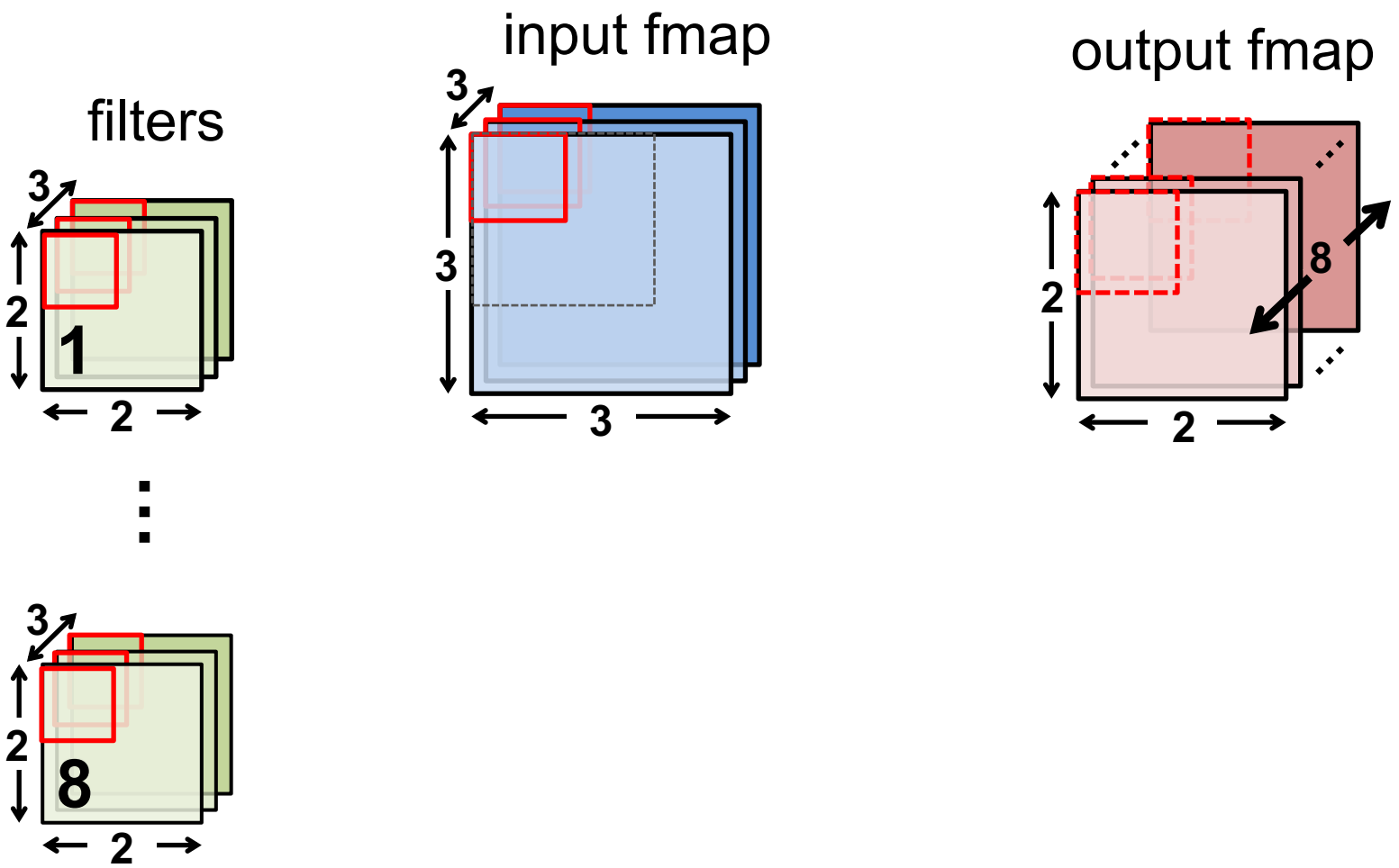
http://nvdla.org

WS Example: NVDLA (simplified)



WS Example: NVDLA (simplified)

Cycle through input and output fmap (hold weights)



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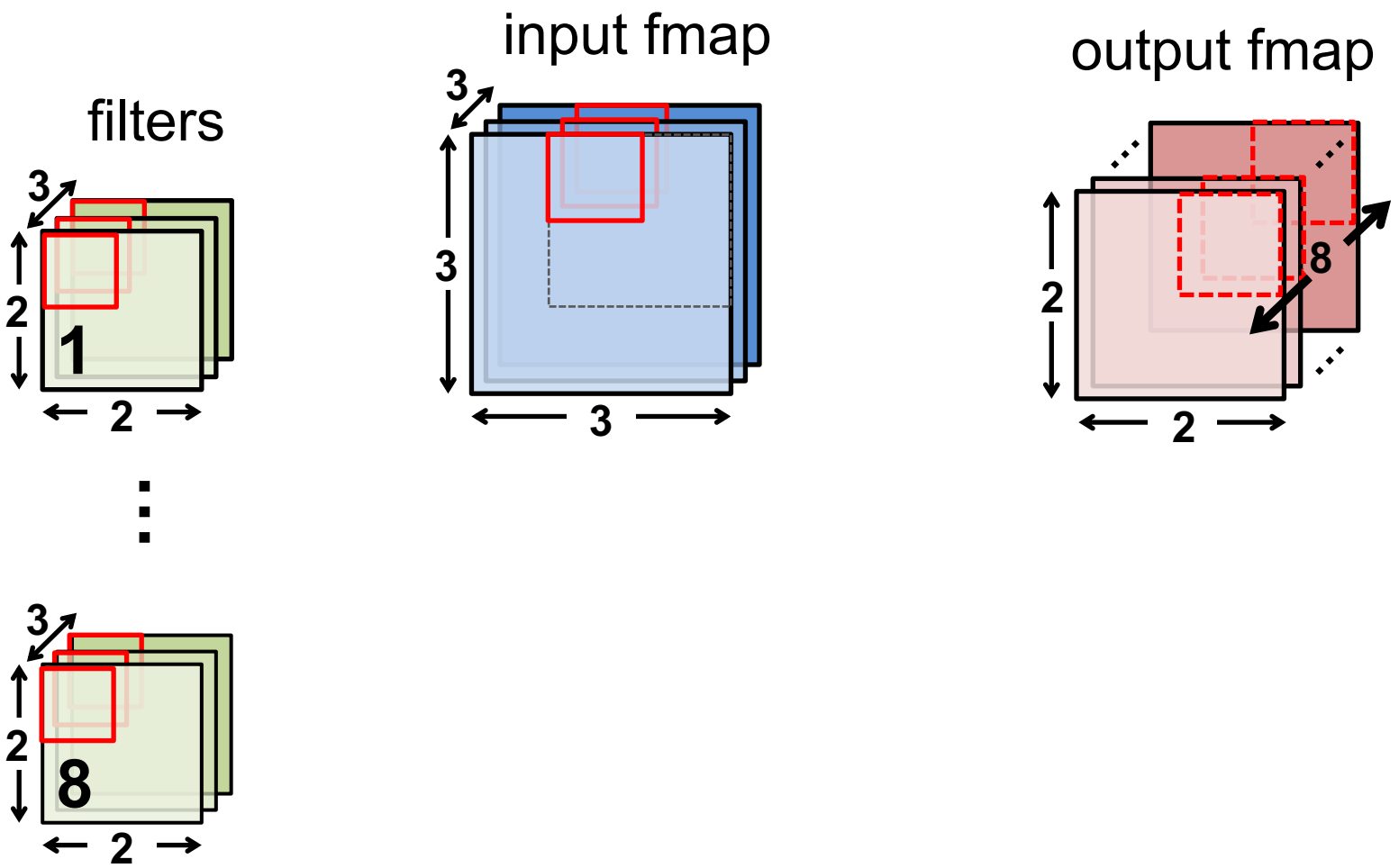
Cycle through input and output fmap (hold weights)



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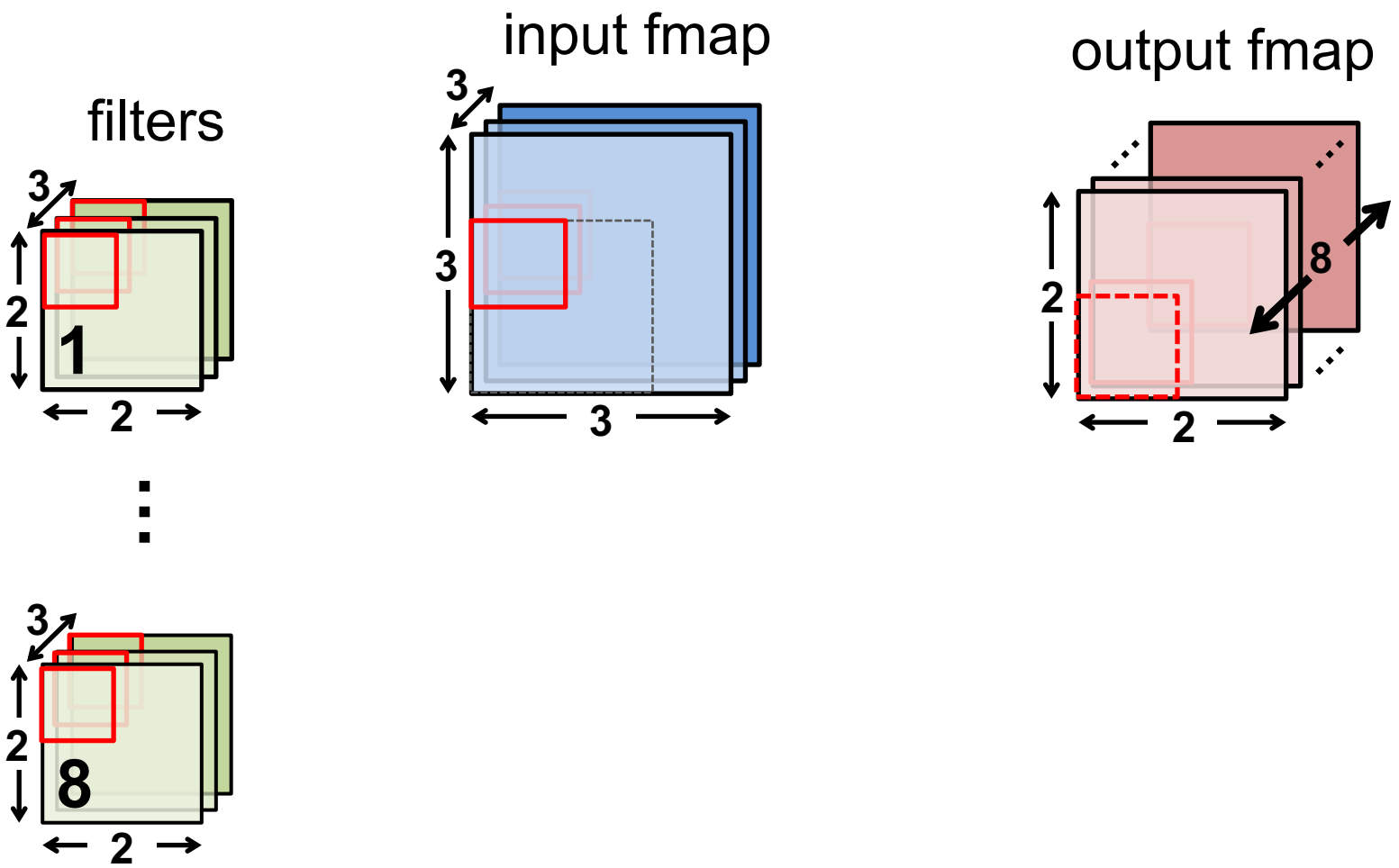
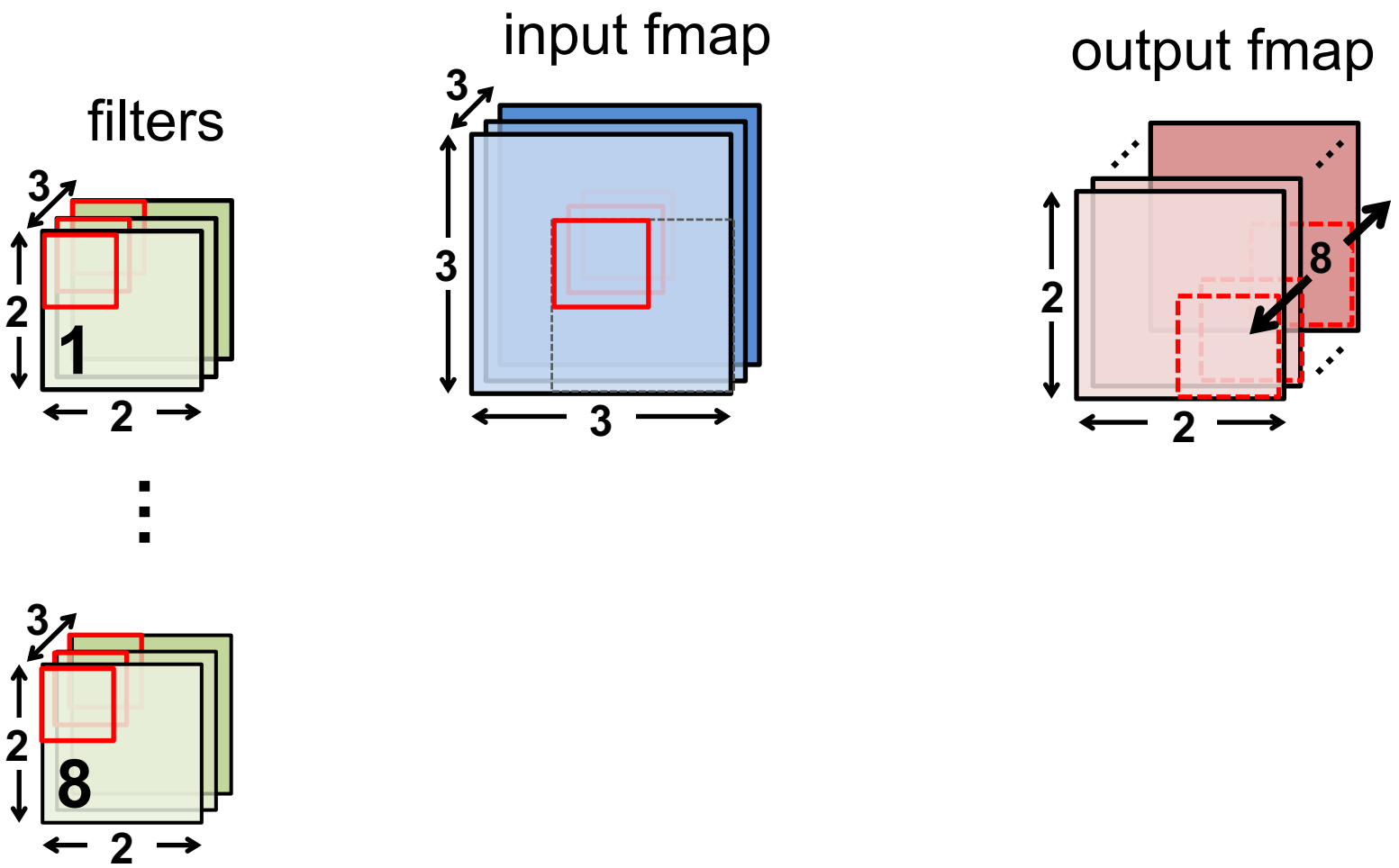


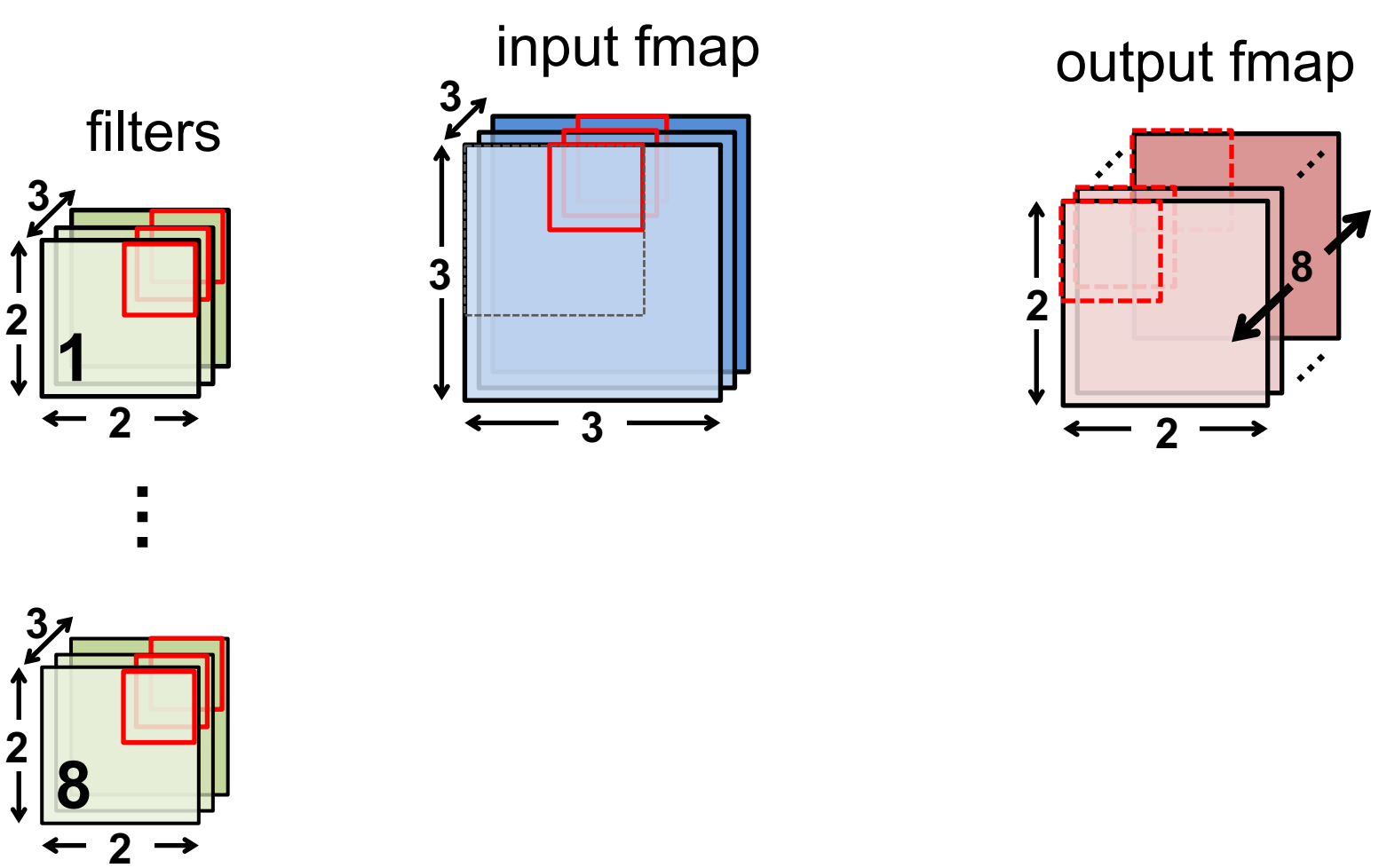
WS Example: NVDLA (simplified)

Cycle through input and output fmap (hold weights)



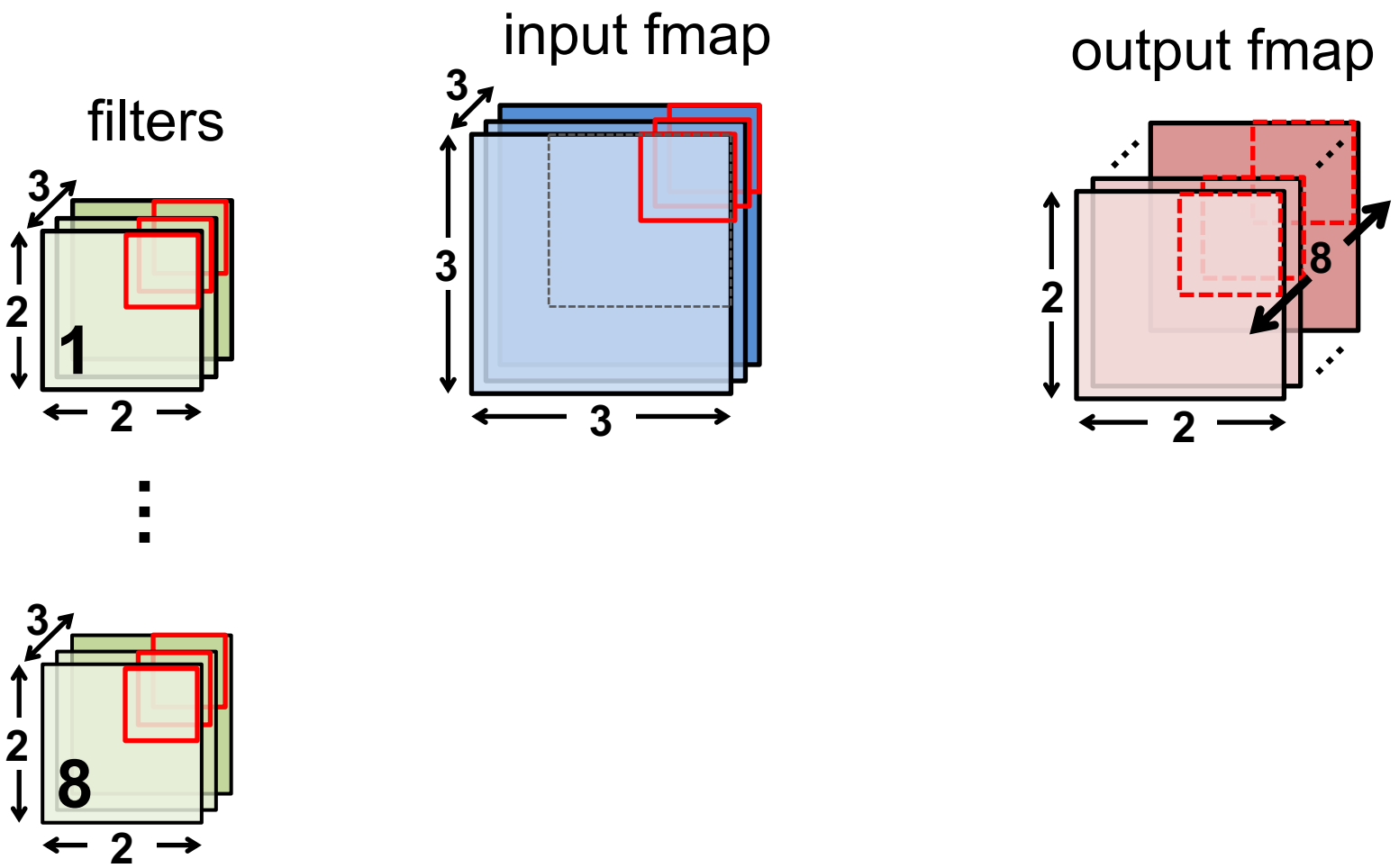
WS Example: NVDLA (simplified)

Load new weights



WS Example: NVDLA (simplified)

Cycle through input and output fmap (hold weights)



Taxonomy: More Examples

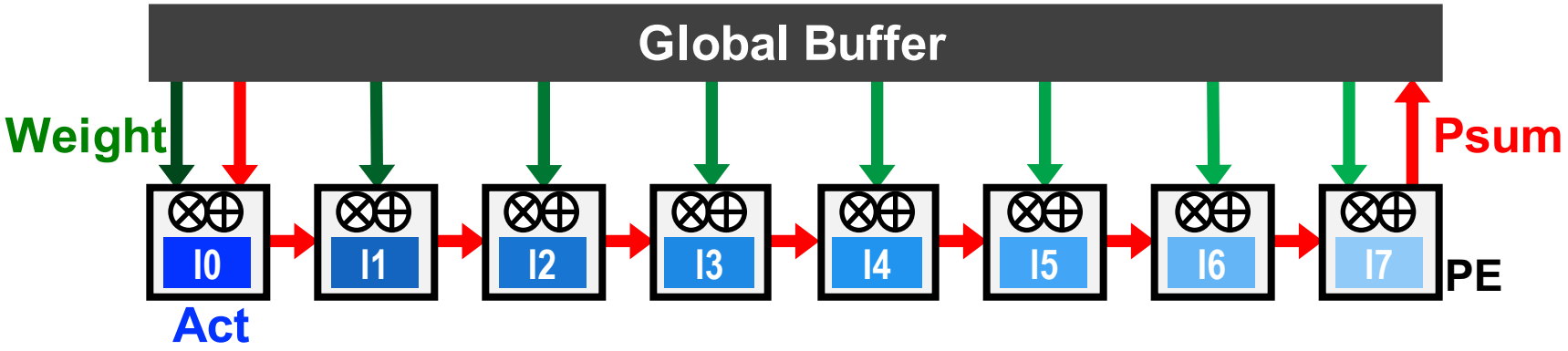
- **Output Stationary (OS)**

  [**Peemen**, *ICCD* 2013] [**ShiDianNao**, *ISCA* 2015]
  [**Gupta**, *ICML* 2015] [**Moons**, *VLSI* 2016] [**Thinker**, *VLSI* 2017]

- **Weight Stationary (WS)**

  [**Chakradhar**, *ISCA* 2010] [**nn-X (NeuFlow)**, *CVPRW* 2014]
  [**Park**, *ISSCC* 2015] [**ISAAC**, *ISCA* 2016] [**PRIME**, *ISCA* 2016]
  [**TPU**, *ISCA* 2017]

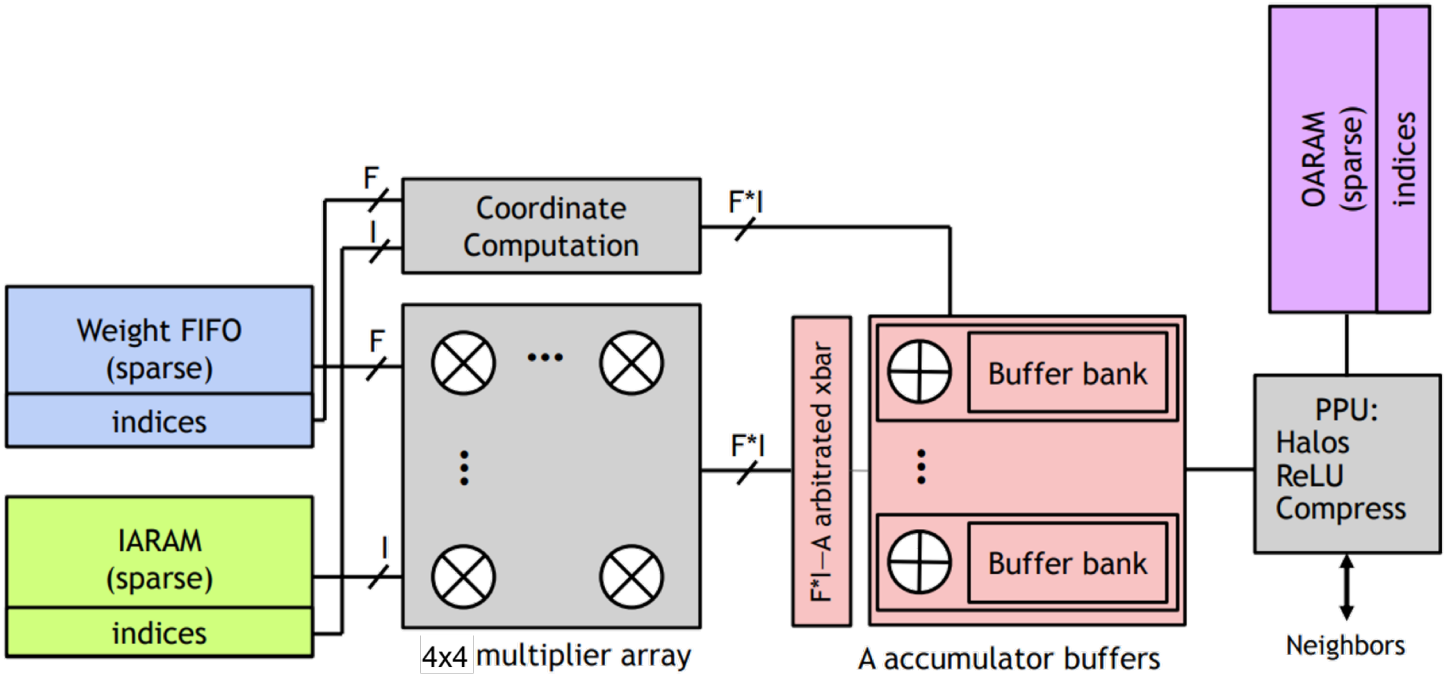
Input Stationary (IS)



- **Minimize activation** read energy consumption
  - maximize convolutional and fmap reuse of activations
- **Unicast weights** and **accumulate psums spatially** across the PE array.

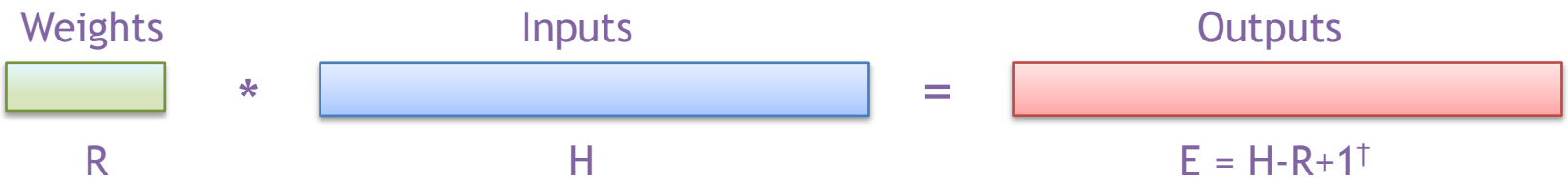
IS Example: SCNN

- Used for sparse CNNs
  - Sparse CNN is where many weights are zeros
  - Activations also have sparsity from ReLU



[Parashar et al., ISCA 2017]

1-D Convolution – Weight Stationary




```
int I[H];      // Input activations
int W[R];      // Filter weights
int O[E];      // Output activations

for (e = 0; e < E; e++)
    for (r = 0; r < R; r++)
        O[e] += I[e+r] * W[r];
```

How can we implement input stationary with no input index?

† Assuming: 'valid' style convolution

1-D Convolution – Input Stationary

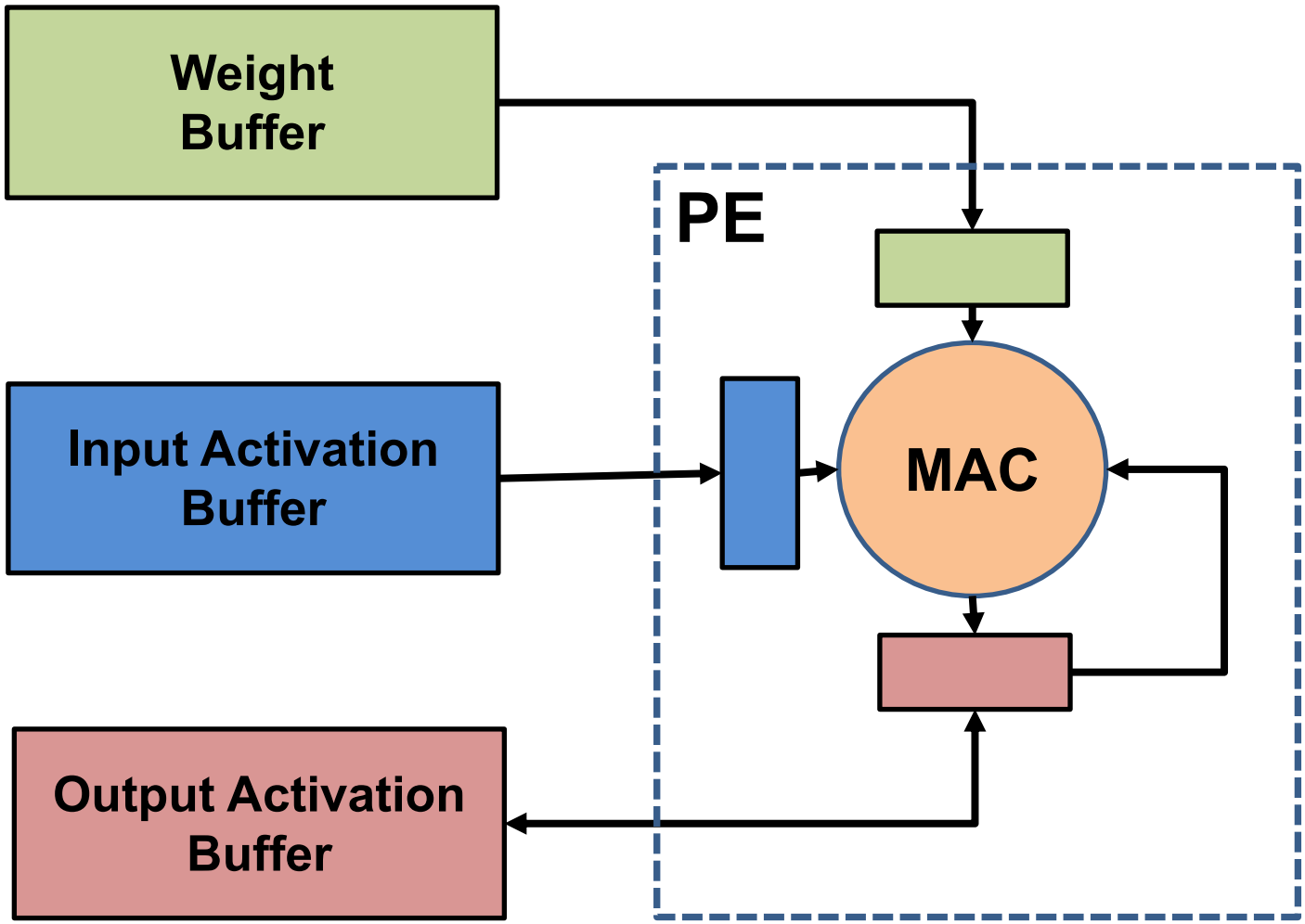

```
int I[H];      // Input activations
int W[R];      // Filter weights
int O[E];      // Output activations

for (h = 0; h < H; h++)
    for (r = 0; r < R; r++)
        O[h-r] += I[h] * W[r];
```

Beware w-r must be >= 0 and <E

† Assuming: 'valid' style convolution

Reference Patterns of Different Dataflows

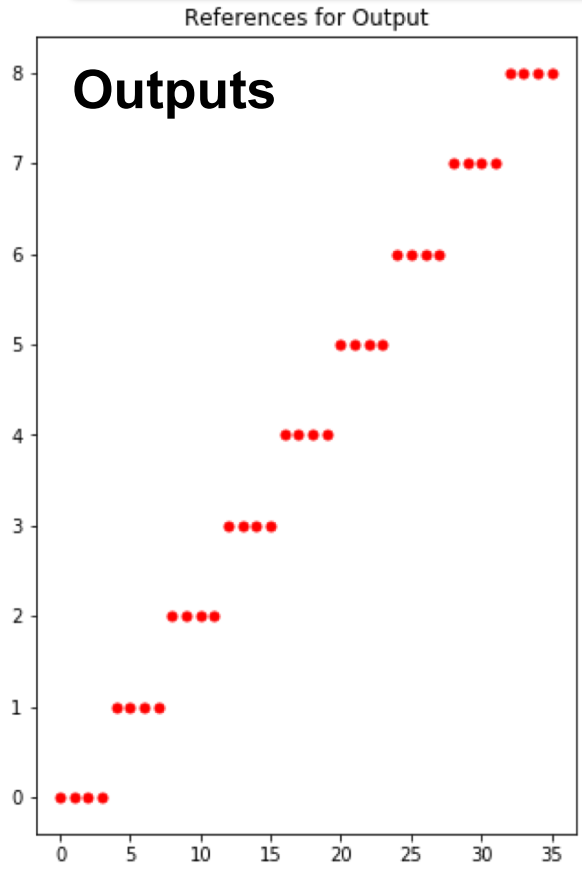
Single PE Setup

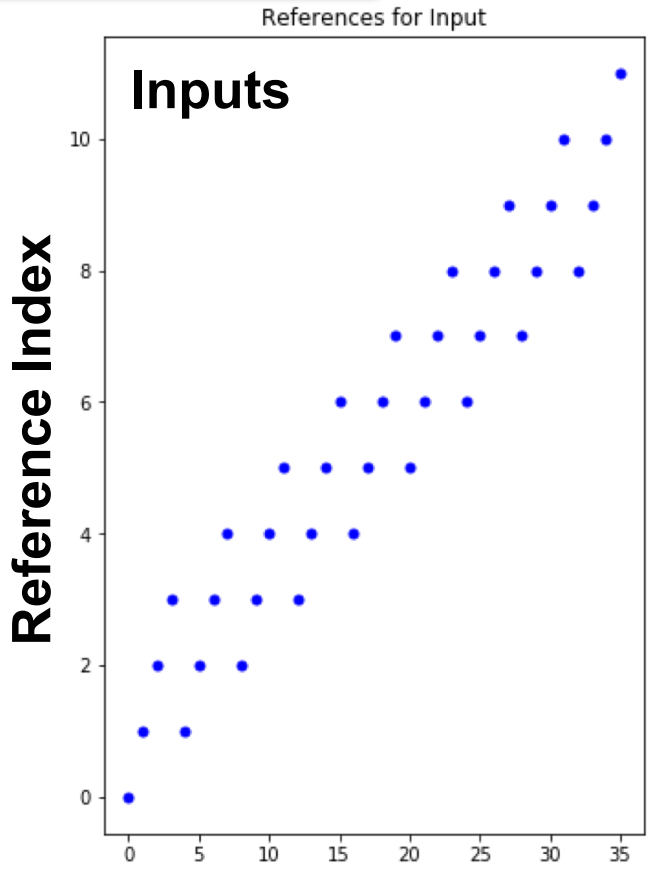


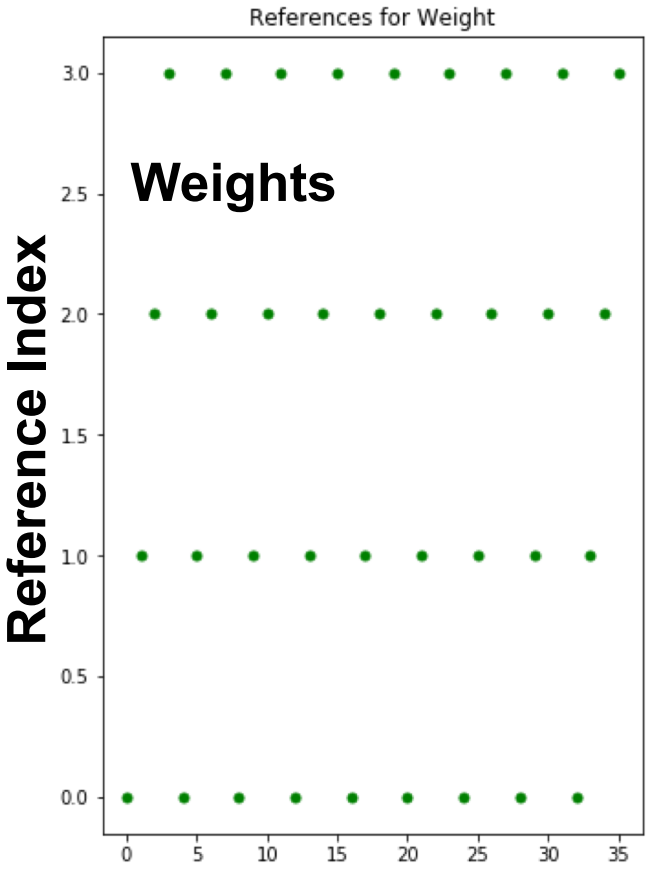
Output Stationary – Reference Pattern

```
for (e = 0; e < E; e++)
  for (r = 0; r < R; r++)
    O[e] += I[e+r] * W[r];
```

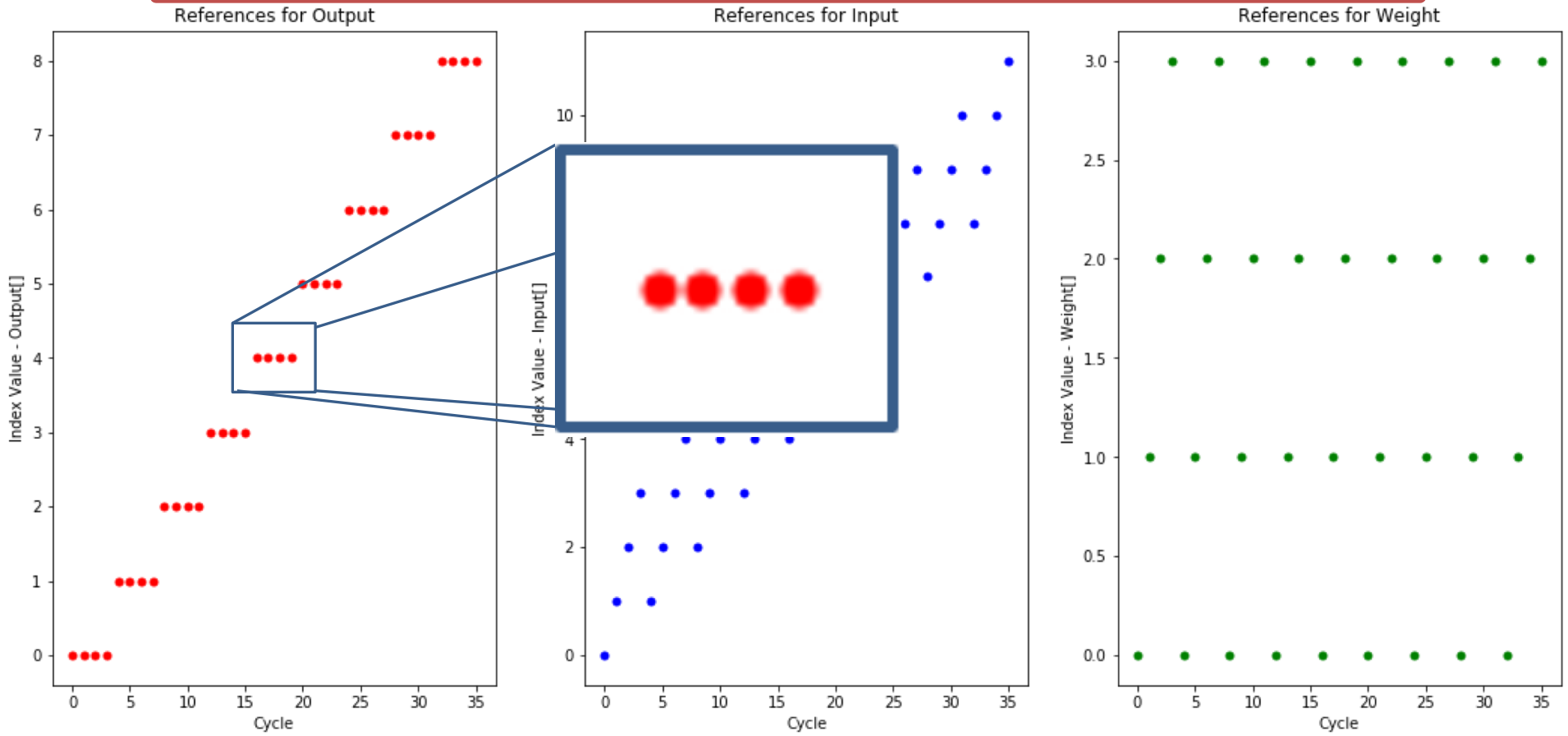
Layer Shape:
- H = 12
- R = 4
- E = 9





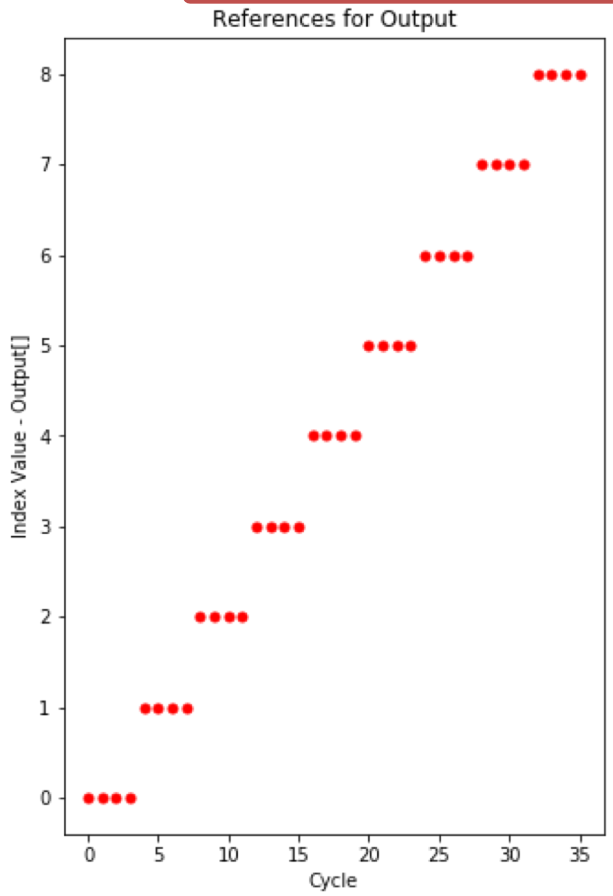


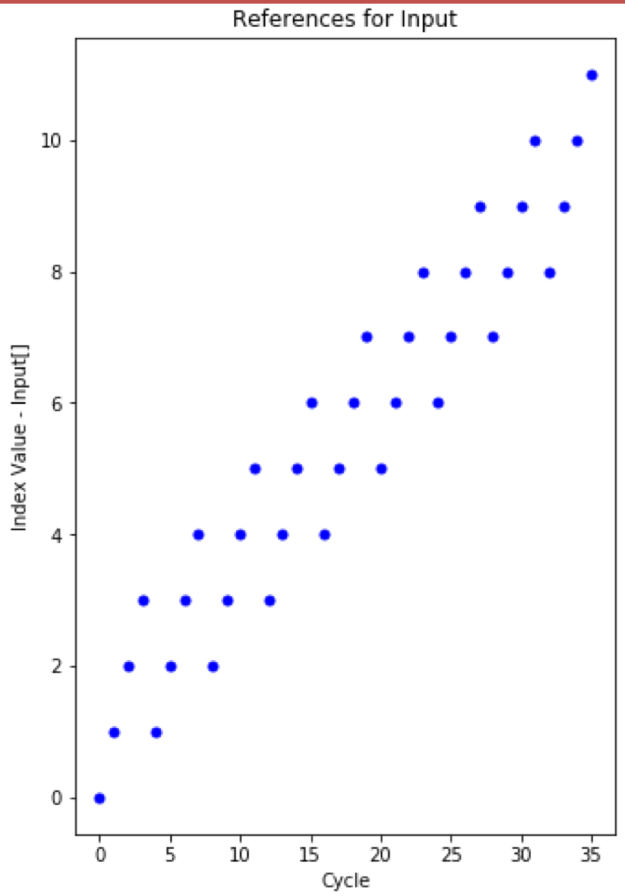
Output Stationary – Reference Pattern

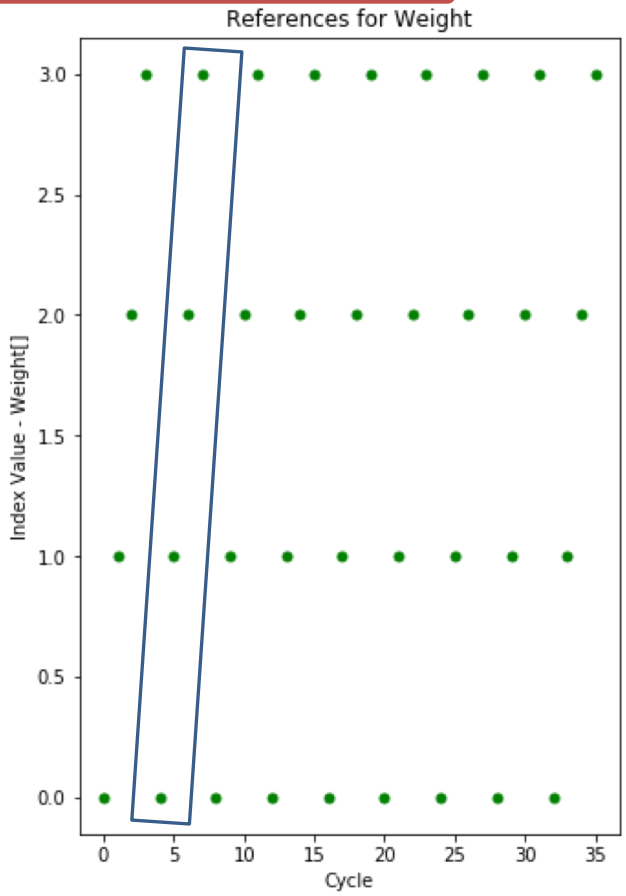


Observations: - Single output is reused many times (R)

Output Stationary – Reference Pattern



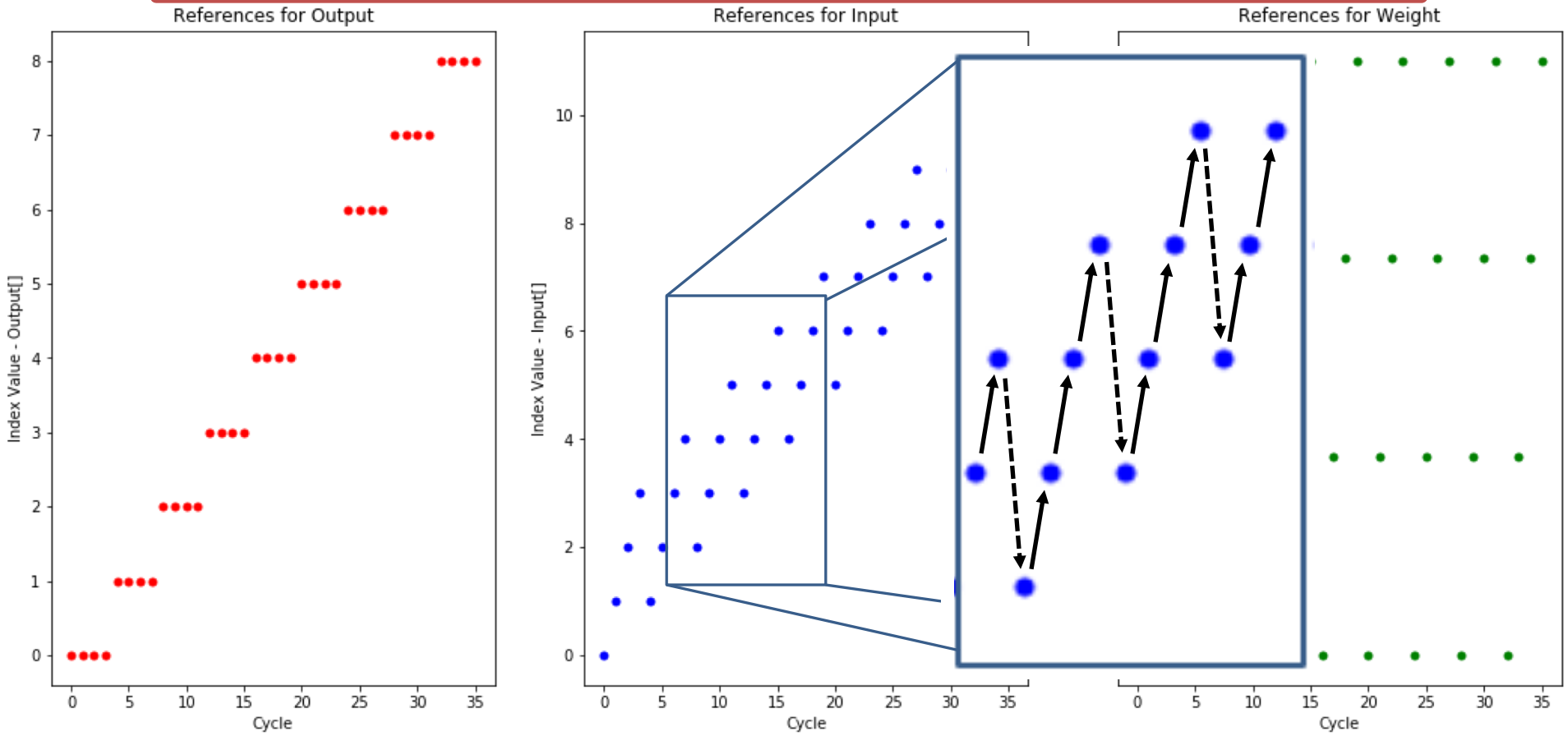




Observations:

- Single output is reused many times (R)
- All weights reused repeatedly

Output Stationary – Reference Pattern



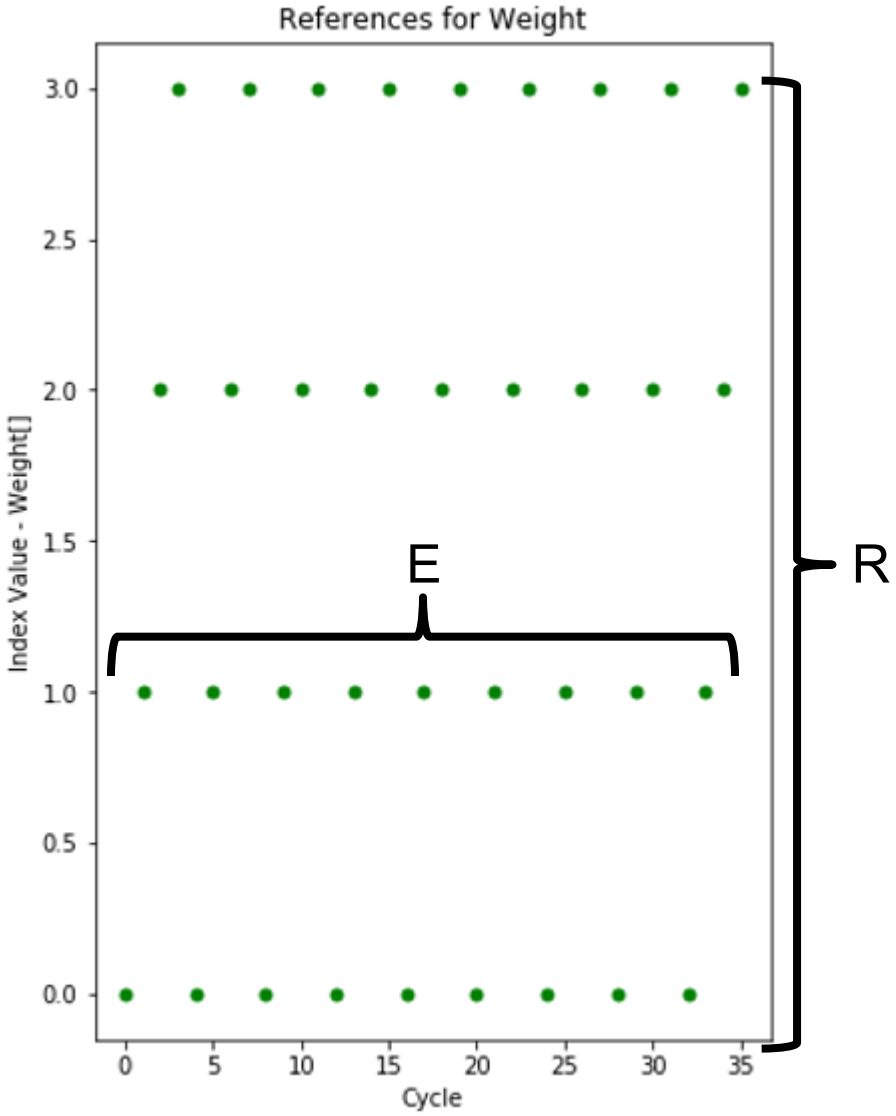
Observations:

- Single output is reused many times (R)
- All weights reused repeatedly
- Sliding window of inputs (size = R)

Buffer Data Accesses - Weights

```
for (e = 0; e < E; e++)
  for (r = 0; r < R; r++)
    O[e] += I[e+r] * W[r];
```

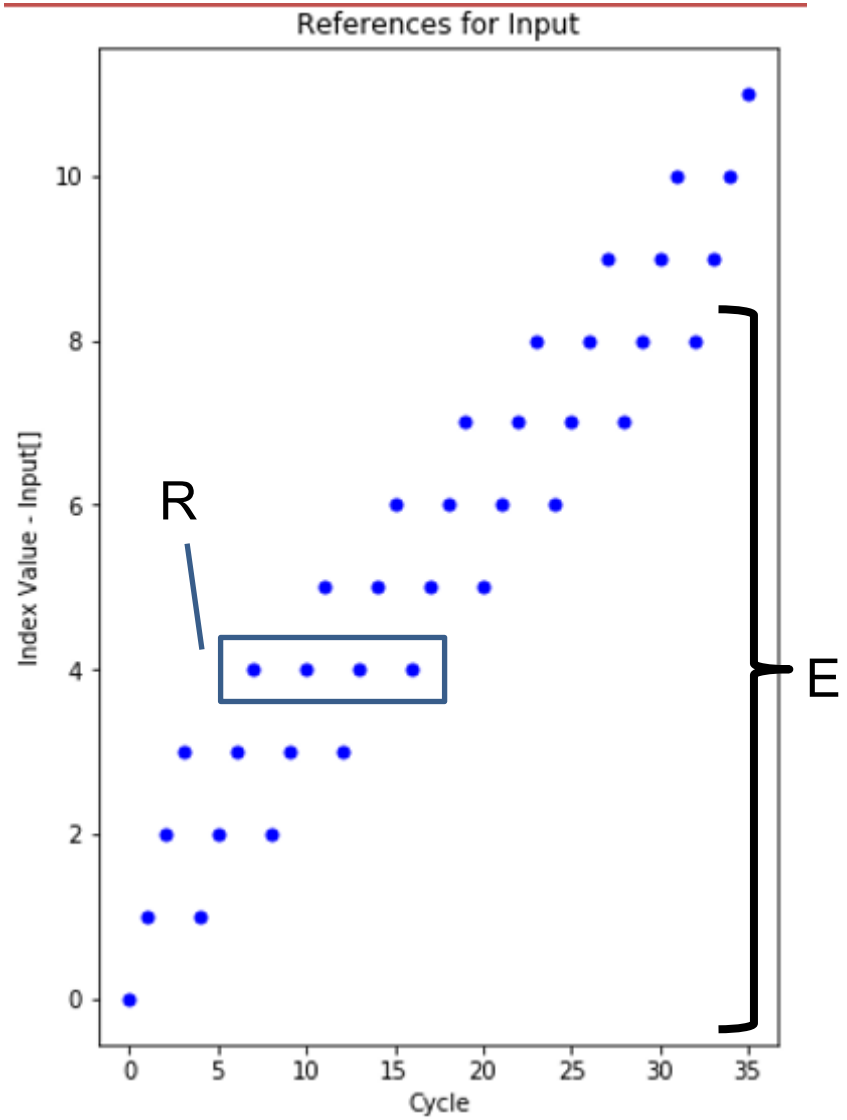
	OS
MACs	E*R
Weight Reads	E*R
Input Reads	
Output Reads	
Output Writes	



Buffer Data Accesses - Inputs

```
for (e = 0; e < E; e++)
  for (r = 0; r < R; r++)
    O[e] += I[e+r] * W[r];
```

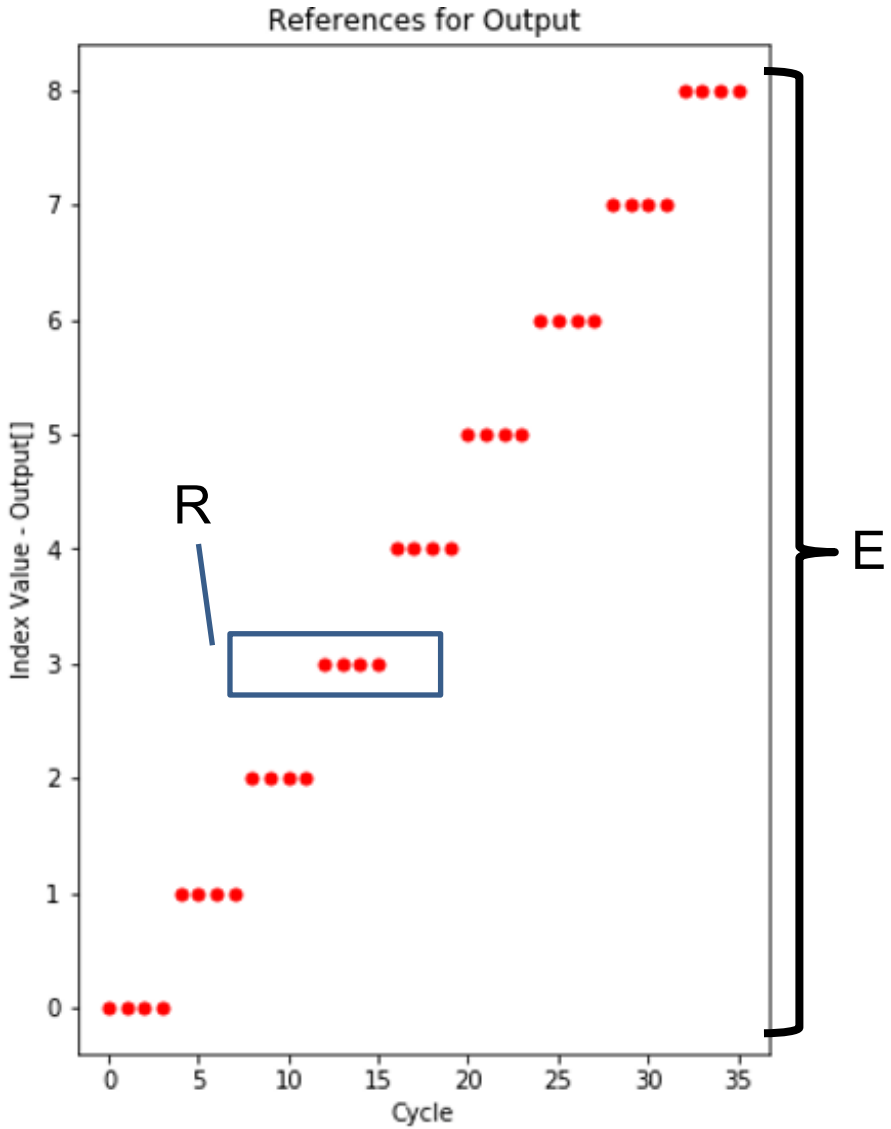
	OS
MACs	E*R
Weight Reads	E*R
Input Reads	E*R
Output Reads	
Output Writes	



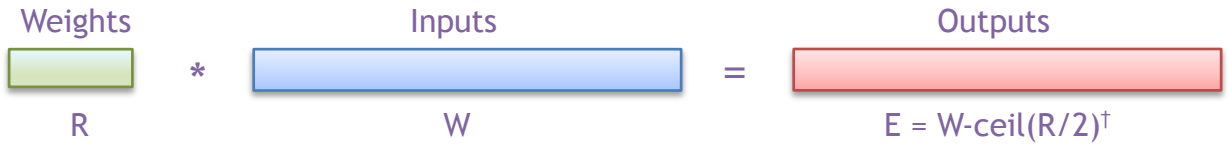
Buffer Data Accesses - Outputs

```
for (e = 0; e < E; e++)
  for (r = 0; r < R; r++)
    O[e] += I[e+r] * W[r];
```

	OS
MACs	E*R
Weight Reads	E*R
Input Reads	E*R
Output Reads	0
Output Writes	E



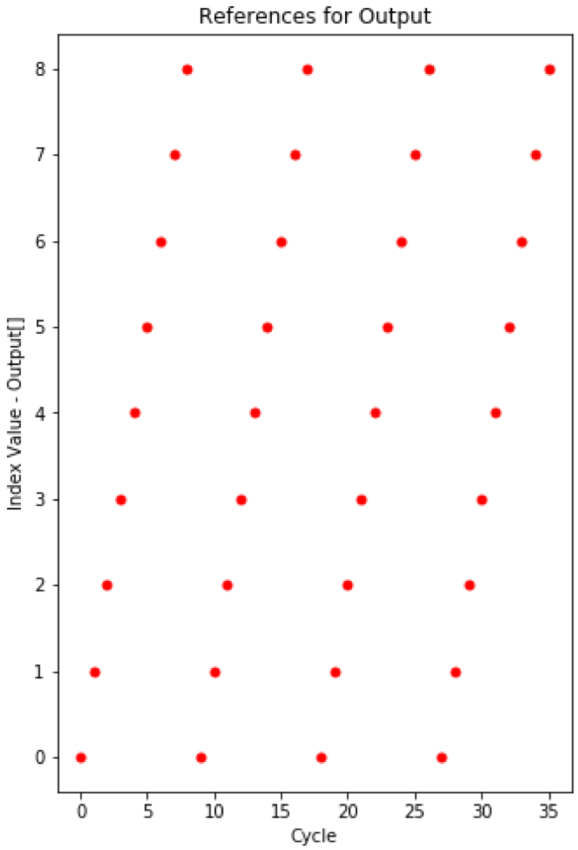
1-D Convolution – Weight Stationary

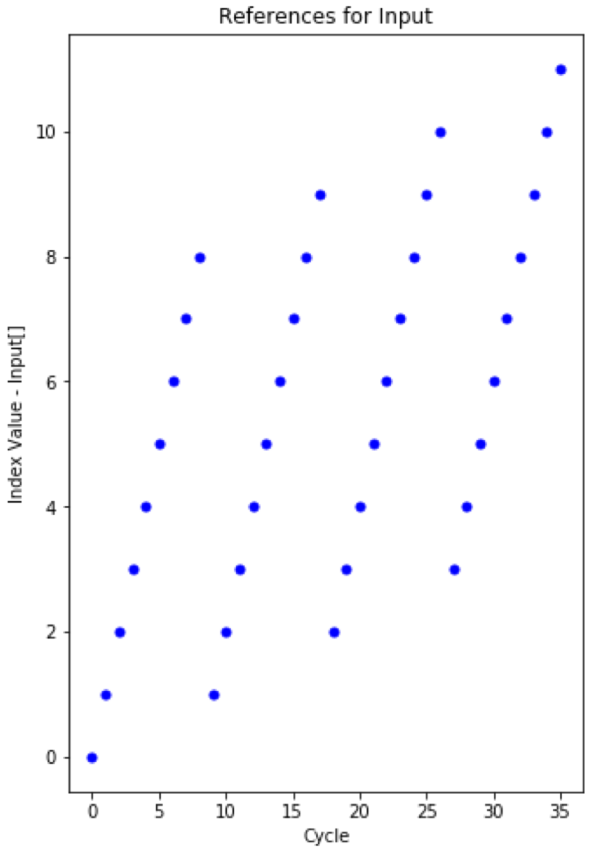


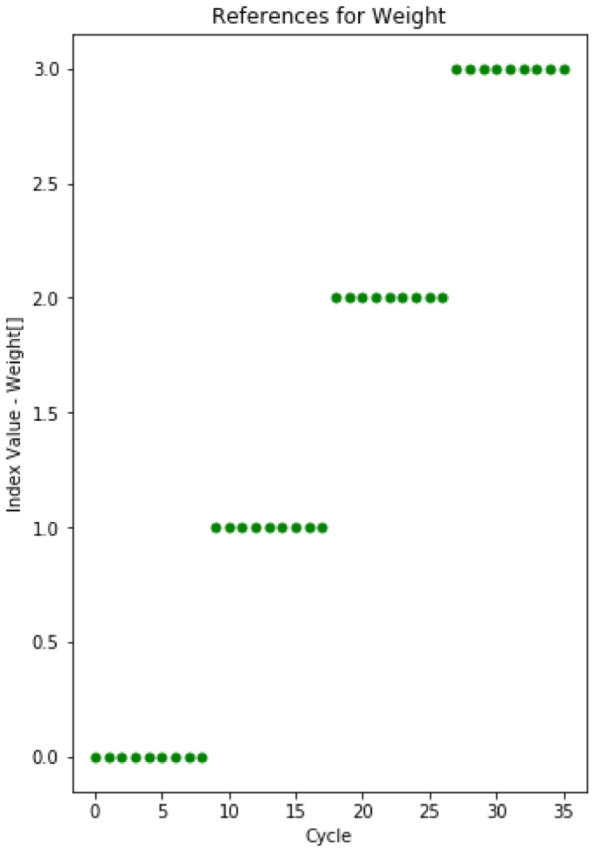

```
int I[H];      // Input activations
int W[R];      // Filter weights
int O[E];      // Output activations

for (e = 0; e < E; e++)
      for (r = 0; r < R; r++)
         O[e] += I[e+r] * W[r];
```

† Assuming: 'valid' style convolution

Weight Stationary – Reference Pattern







Observations:

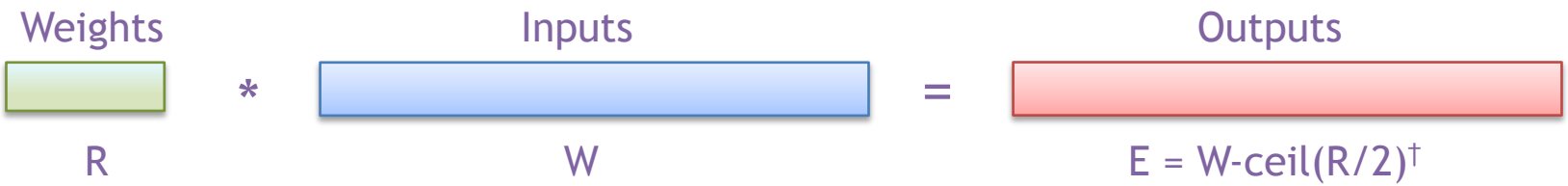
- Single weight is reused many times (E)
- Large sliding window of inputs (size = E)
- Fixed window of outputs (size = E)

L1 Weight Stationary - Costs

```
for (r = 0; r < R; r++)
    for (e = 0; e < E; e++)
        O[e] += I[e+r] * W[r];
```

	OS	WS		
MACs	E*R	E*R		
Weight Reads	E*R	R		
Input Reads	E*R	E*R		
Output Reads	0	E*R		
Output Writes	E	E*R		

1-D Convolution – Input Stationary

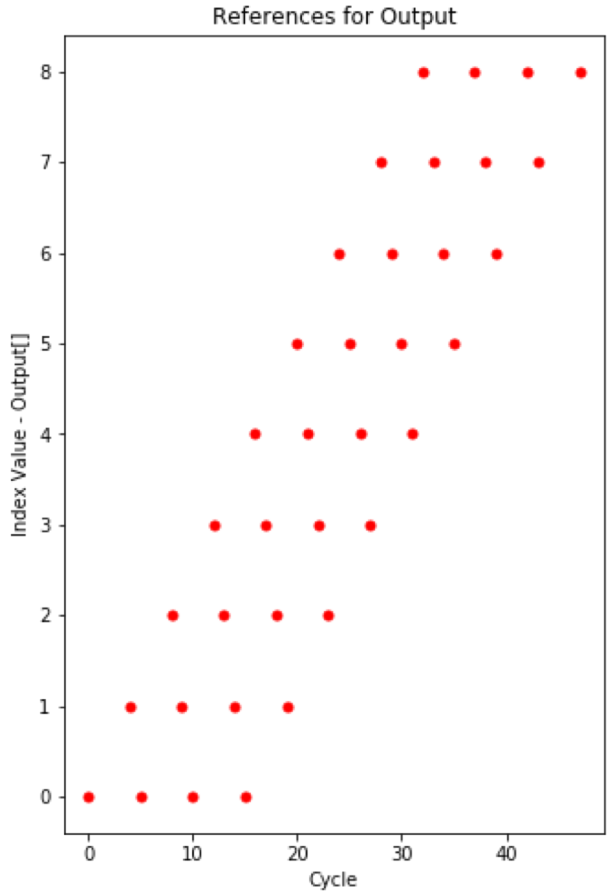


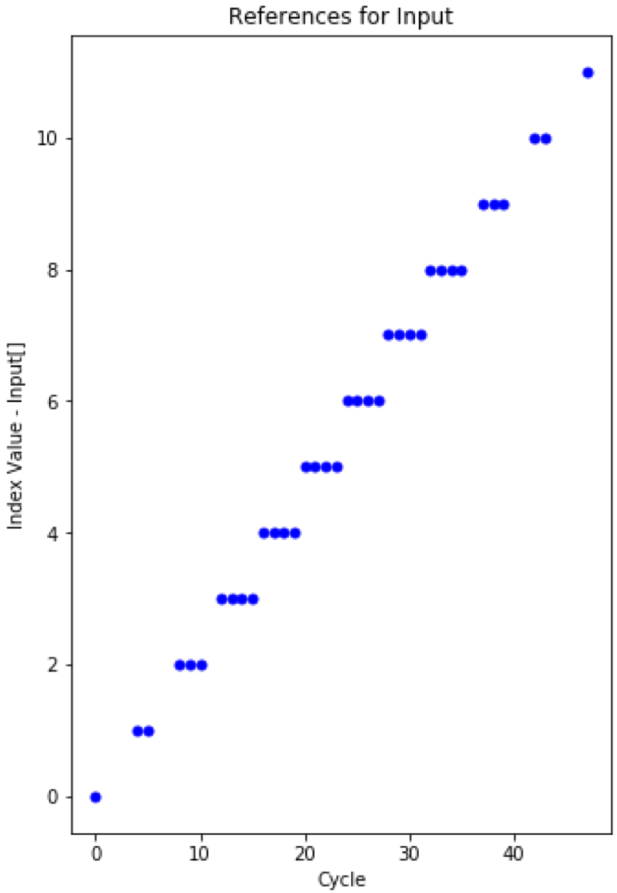

```
int I[H];      // Input activations
int W[R];      // Filter weights
int O[E];      // Output activations

for (h = 0; h < H; h++)
    for (r = 0; r < R; r++)
        O[h-r] += I[h] * W[r];
```

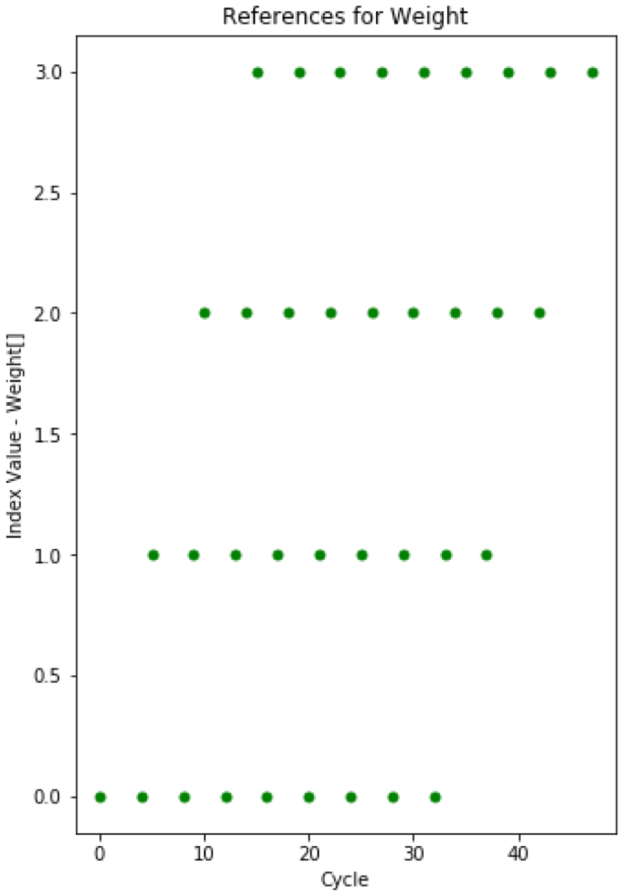
Beware w-r must be >= 0 and <E

† Assuming: 'valid' style convolution

Input Stationary – Reference Pattern







Observations:

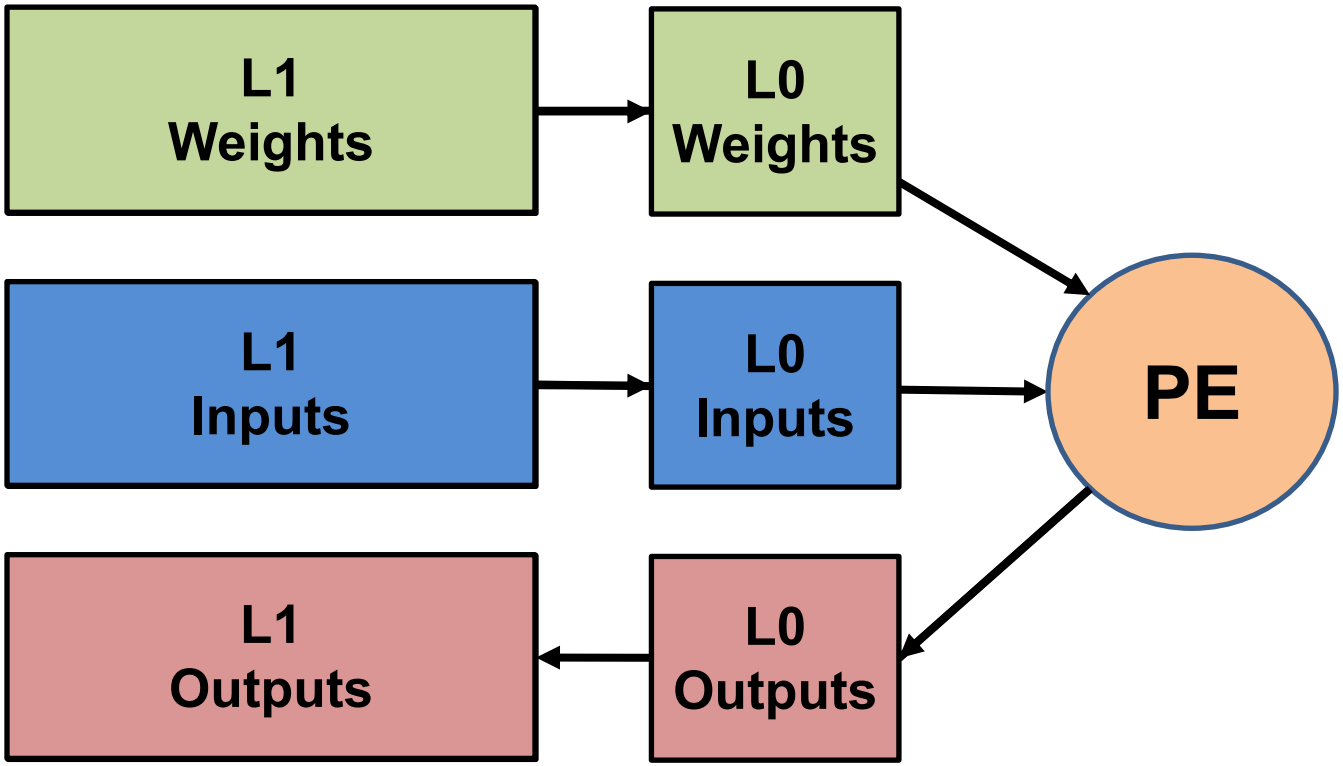
- Inputs used repeatedly (R times)
- Weights reused in large window (size = R)
- Sliding window of outputs (size = R)

Minimum Costs

	OS	WS	IS	Min
MACs	E*R	E*R	E*R	E*R
Weight Reads	E*R	R	E*R	R
Input Reads	E*R	E*R	E	E
Output Reads	0	E*R	E*R	0
Output Writes	E	E*R	E*R	E

Assume: W ~= E

Intermediate Buffering



1-D Convolution – Buffered


```
int I[H];      // Input activations
int W[R];      // Filter Weights
int O[E];      // Output activations

// Level 1
for (e1 = 0; e1 < E1; e1++)
  for (r1 = 0; r1 < R1; r1++)
    // Level 0
    for (e0 = 0; e0 < E0; e0++)
      for (r0 = 0; r0 < R0; r0++)
          O[e1*E0+e0] += I[e1*E0+e0 + r1*R0+r0]
                       * W[r1*R0+r0];
```

Note E and R are factored so:
E0*E1 = E
R0*R1 = R

† Assuming: 'valid' style convolution

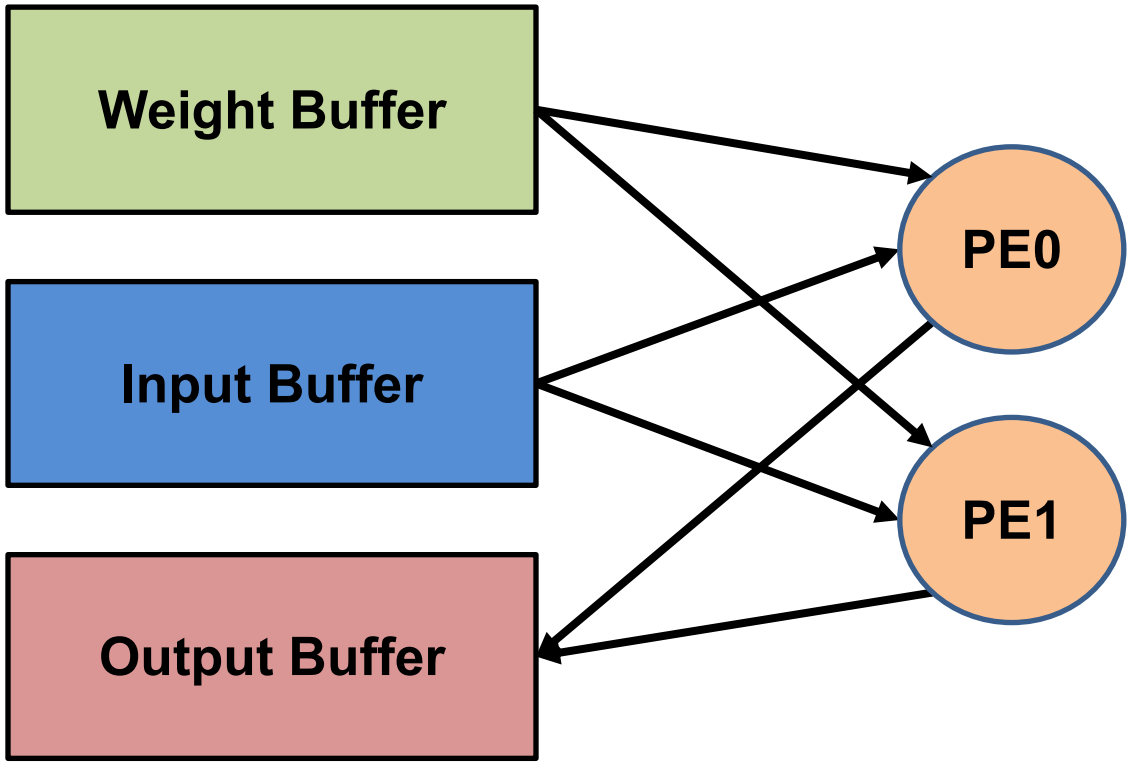
Buffer sizes

```
// Level 1
for (e1 = 0; e1 < E1; e1++)
  for (r1 = 0; r1 < R1; r1++)
    // Level 0
    for (e0 = 0; e0 < E0; e0++)
      for (r0 = 0; r0 < R0; r0++)
          O[e1*E0+e0] += I[e1*E0+e0 + r1*R0+r0] * W[r1*R0+r0];
```

- Level 0 buffer size is volume needed in each Level 1 iteration.
- Level 1 buffer size is volume needed to be preserved and re-delivered in future (usually successive) Level 1 iterations.

A legal assignment of loop limits will fit into the hardware's buffer sizes

Spatial PEs



1-D Convolution – Spatial


```
int I[W];      // Input activations
int W[R];      // Filter Weights
int O[E];      // Output activations

// Level 1
for (r1 = 0; r1 < R1; r1++)
  for (e1 = 0; e1 < E1; e1++)
    // Level 0
    spatial-for (r0 = 0; r0 < R0; r0++)
      spatial-for (e0 = 0; e0 < E0; e0++)
        O[e1*E0+e0] += I[e1*E0+e0 + r1*R0+r0]
                     * W[r1*R0+r0];
```

Note:
- E0*E1 = E
- R0*R1 = R
- R0*E0 <= #PEs

† Assuming: 'valid' style convolution

Summary of DNN Dataflows

- Minimizing **data movement** is the key to achieving high **energy efficiency** for DNN accelerators
- Dataflow taxonomy:
  - **Output Stationary**: minimize movement of psums
  - **Weight Stationary**: minimize movement of weights
  - **Input Stationary**: minimize movement of inputs
- **Loop nest** provides a compact way to describe various properties of a dataflow, e.g., data tiling in multi-level storage and spatial processing.