EE-508: Hardware Foundations for Machine Learning
Modeling Accelerators

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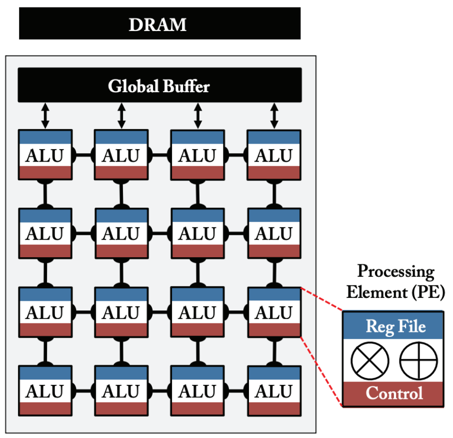
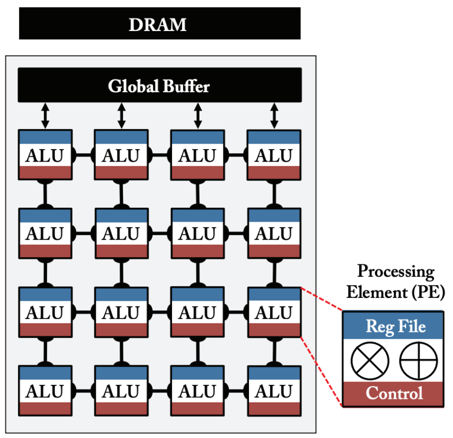
Modeling Accelerators

Modeling

- High Level Languages
  - Python, C/C++
- Domain-Specific Languages (DSLs).
  - Examples:
    - Halide:
      - Allows separation of the algorithm from its schedule, enabling performance portability across different hardware architectures.
    - TVM:
      - Open-source compiler framework that abstracts the details of hardware accelerators.
- Hardware Description Languages (HDLs):
  - SystemC, SystemVerilog, VHDL
  - HLS (High-Level Synthesis) Languages



Modeling



- High Level Languages
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- Domain-Specific Languages (DSLs).
  - Examples:
    - Halide:
      - Allows separation of the algorithm from its schedule, enabling performance portability across different hardware architectures.
    - TVM:
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- Hardware Description Languages (HDLs):
  - SystemC, SystemVerilog, VHDL
  - HLS (High-Level Synthesis) Languages

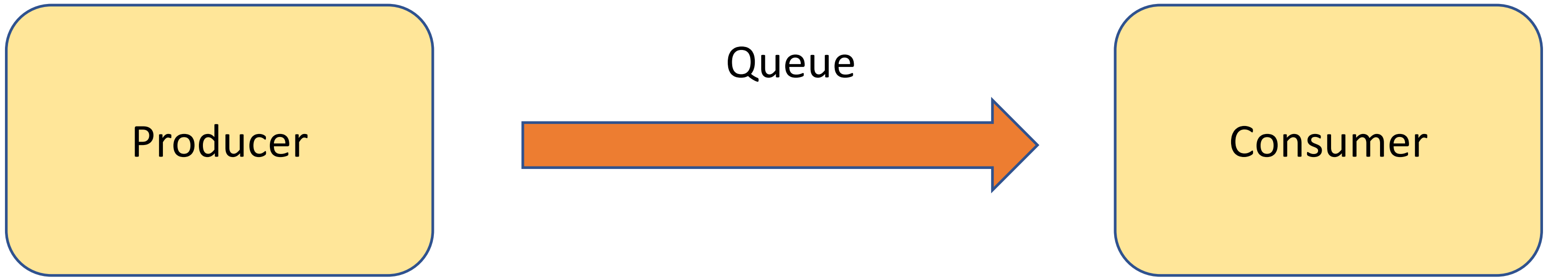
It's more common to use HDLs for hardware design, but we use Python for high level modeling for simplicity.

Python Multiprocessing: Using Process and Queue

- Process:
  - A class for spawning processes in Python, similar to threading.
- Queue:
  - A safe way to pass messages between processes.
    - The maximum size depends on the OS.

```python
def producer(queue):
    for i in range(5):
        item = f'Item {i}'
        queue.put(item)
        print(f'Produced {item}')
        time.sleep(1)
```

```python
def consumer(queue):
    while True:
        item = queue.get()
        if item is None:
            break
        print(f'Consumed {item}')
        time.sleep(1.5)
```

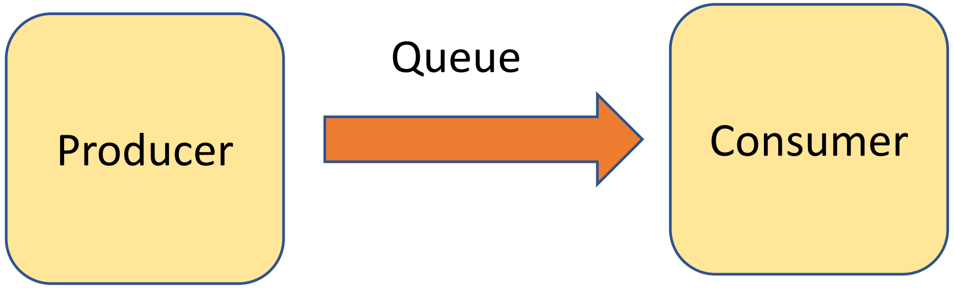


The Put Function

- `put(item[, block[, timeout]]):`
  - Used to enqueue (or add) an item to the queue.
  - Optionally, you can specify whether to **block** if the queue is full using the block parameter (**default is True**).
    - If block is set to True and the queue is full, the method will wait until there's space available in the queue.
  - `timeout` parameter specifies the maximum amount of time (in seconds) to wait if blocking is enabled.
    - If the timeout is reached and the queue is still full, a `Queue.Full` exception will be raised.

```python
def producer(queue):
    for i in range(5):
        item = f'Item {i}'
        queue.put(item)
        print(f'Produced {item}')
        time.sleep(1)
```

```python
def consumer(queue):
    while True:
        item = queue.get()
        if item is None:
            break
        print(f'Consumed {item}')
        time.sleep(1.5)
```

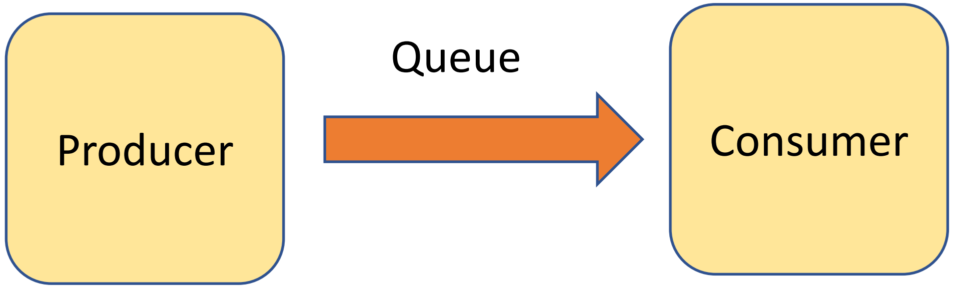


The Get Function

- `get([block[, timeout]]):`
  - Used to dequeue (or retrieve) an item from the queue.
  - Optionally, you can specify whether to **block** if the queue is empty using the block parameter (**default is True**).
    - If block is set to True and the queue is empty, the method will wait until there's an item available in the queue.
  - `timeout` parameter specifies the maximum amount of time (in seconds) to wait if blocking is enabled.
    - If the timeout is reached and the queue is still empty, a `Queue.Empty` exception will be raised.

```
def producer(queue):
    for i in range(5):
        item = f'Item {i}'
        queue.put(item)
        print(f'Produced {item}')
        time.sleep(1)
```

```
def consumer(queue):
  while True:
    item = queue.get()
    if item is None:
        break
    print(f'Consumed {item}')
    time.sleep(1.5)
```



No Wait Version of Put and Get

- `put_nowait(item)`:
  - Similar to put(), but it does not block.
  - It attempts to enqueue the item into the queue immediately.
    - If the queue is full, it raises a queue.Full exception immediately rather than waiting for space to become available.
- `get_nowait()`:
  - Similar to get(), but it does not block.
  - It attempts to dequeue an item from the queue immediately.
    - If the queue is empty, it raises a queue.Empty exception immediately rather than waiting for an item to become available.

Python Multithreading: Using Thread and Queue

```python
def producer(queue):
    for i in range(5):
        item = f'Item {i}'
        queue.put(item)
        print(f'Produced {item}')
        time.sleep(1)
```

```python
def consumer(queue):
 while True:
    item = queue.get()
    if item is None:
        break
    print(f'Consumed {item}')
    time.sleep(1.5)
```

```python
if __name__ == '__main__':
    q = queue.Queue()
    p = threading.Thread(target=producer, args=(q,))
    c = threading.Thread(target=consumer, args=(q,))

    p.start()
    c.start()

    p.join()
    q.put(None) # Signal the consumer to terminate
    c.join()
```

Python Multiprocessing: Using Process and Queue

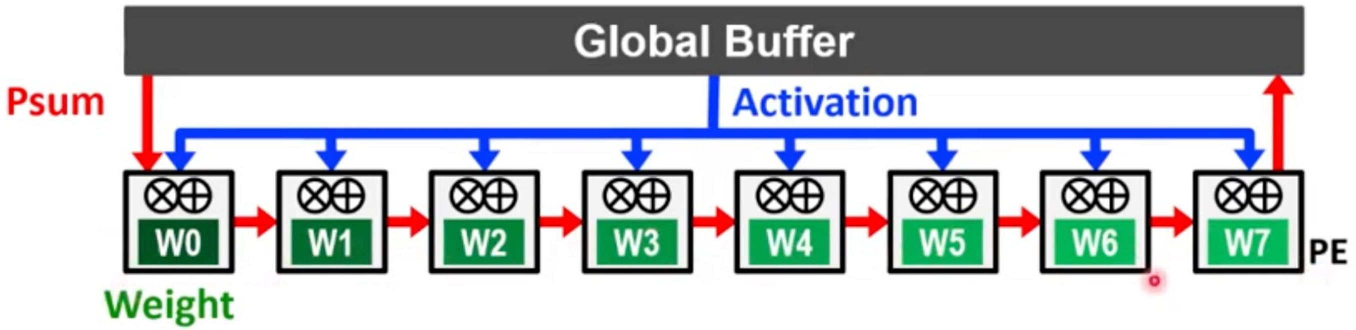
```python
def producer(queue):
    for i in range(5):
        item = f'Item {i}'
        queue.put(item)
        print(f'Produced {item}')
        time.sleep(1)
```

```python
def consumer(queue):
  while True:
      item = queue.get()
      if item is None:
          break
      print(f'Consumed {item}')
      time.sleep(1.5)
```

```python
if __name__ == '__main__':
    q = Queue()
    p = Process(target=producer, args=(q,))
    c = Process(target=consumer, args=(q,))
    p.start()
    c.start()
    p.join()
    q.put(None) # Signal the consumer to terminate
    c.join()
```

Can be run on multiple cores

What Does Each PE Do?



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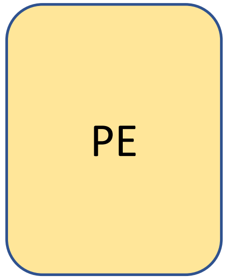

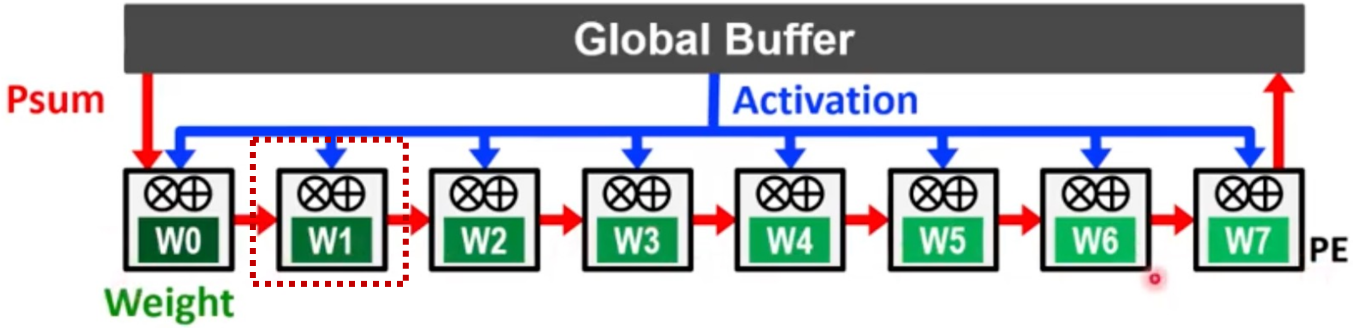

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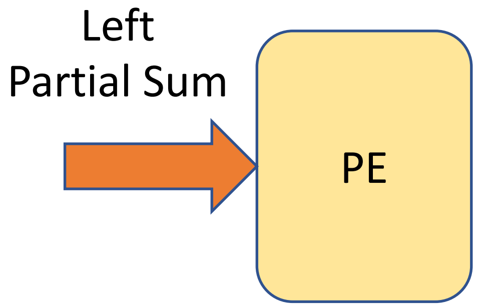

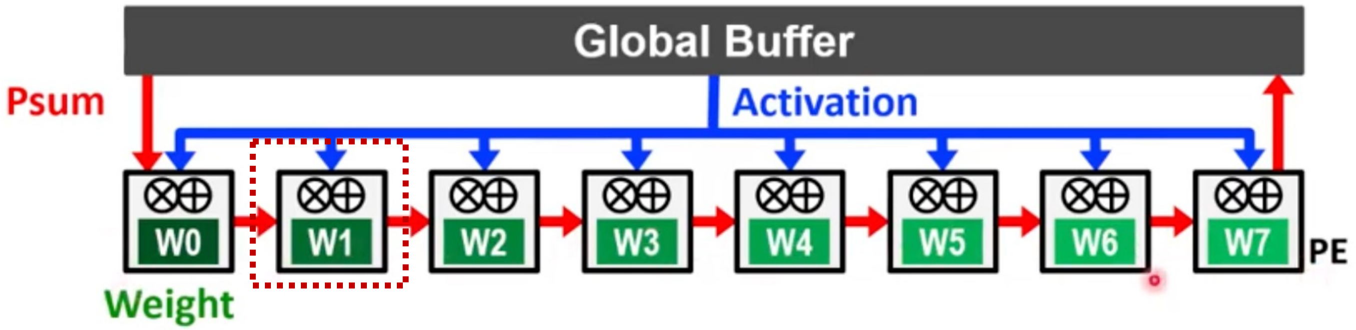

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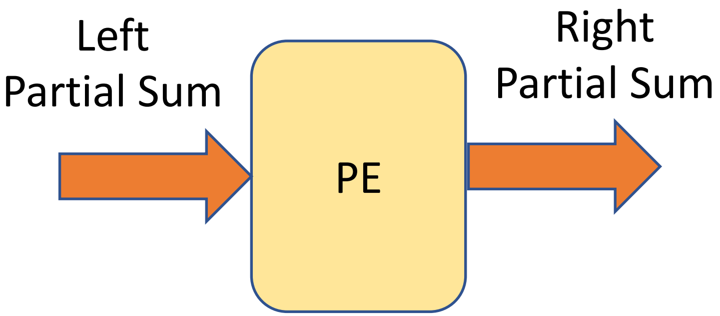

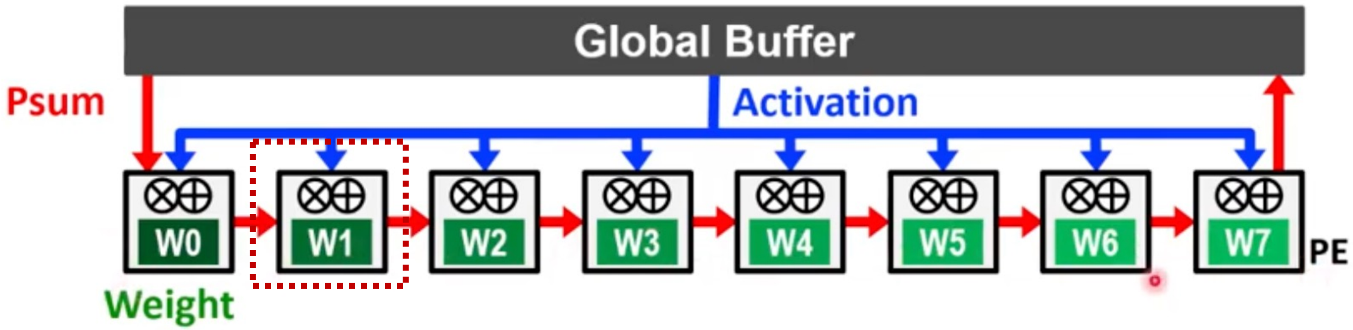

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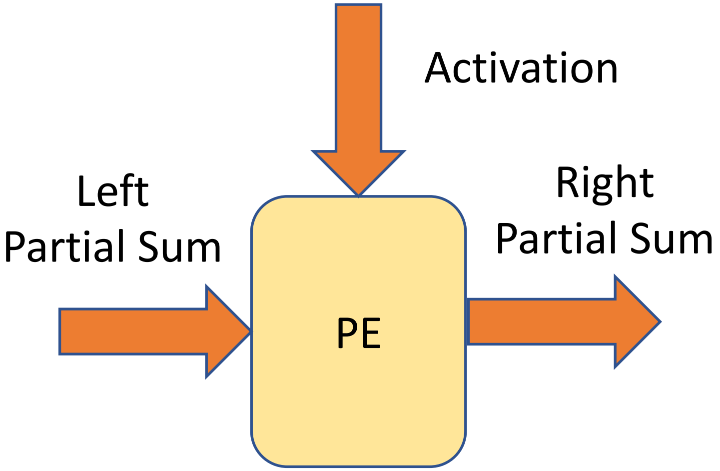

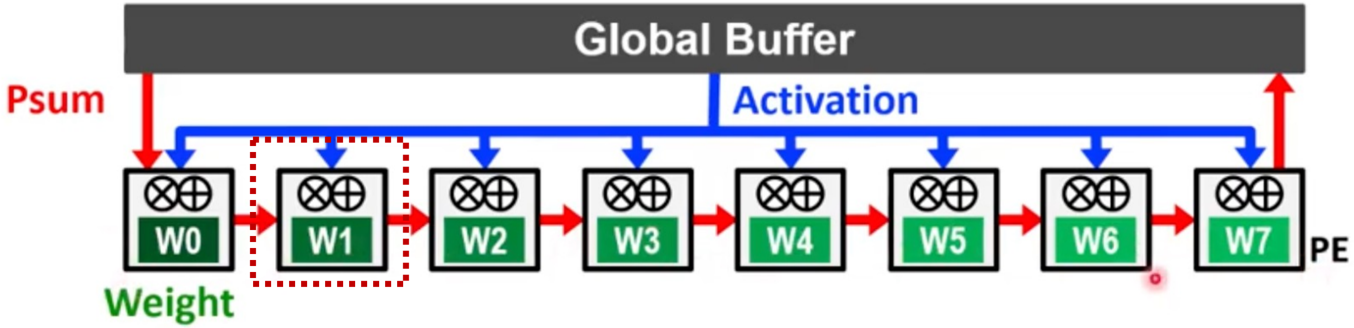

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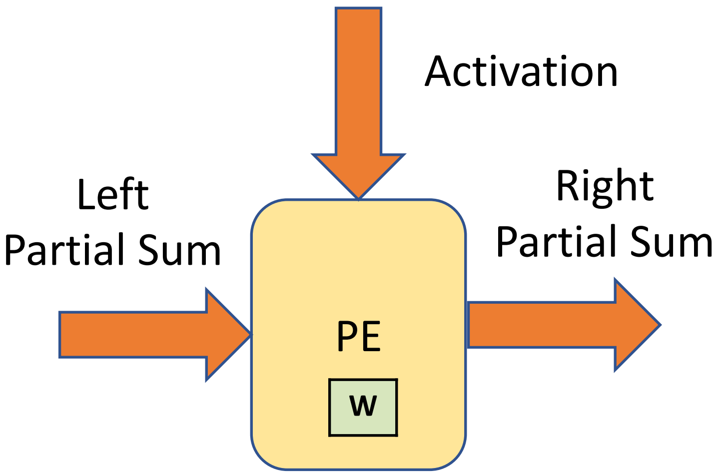

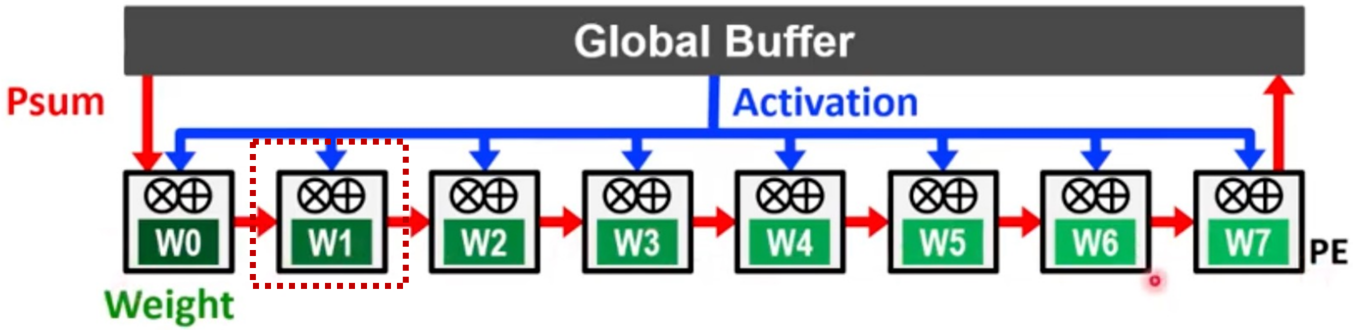

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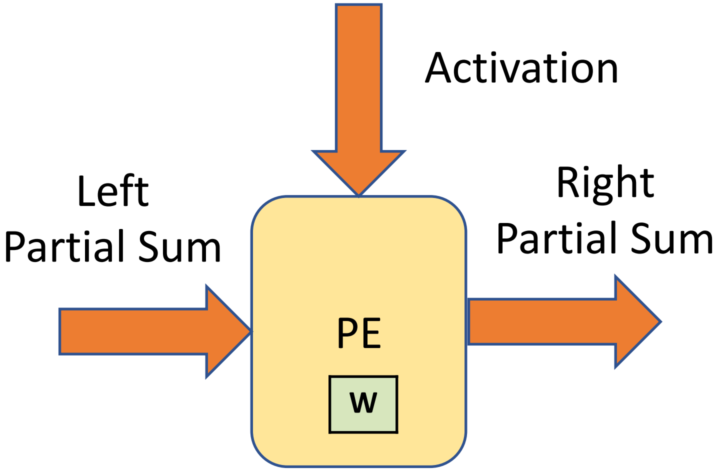

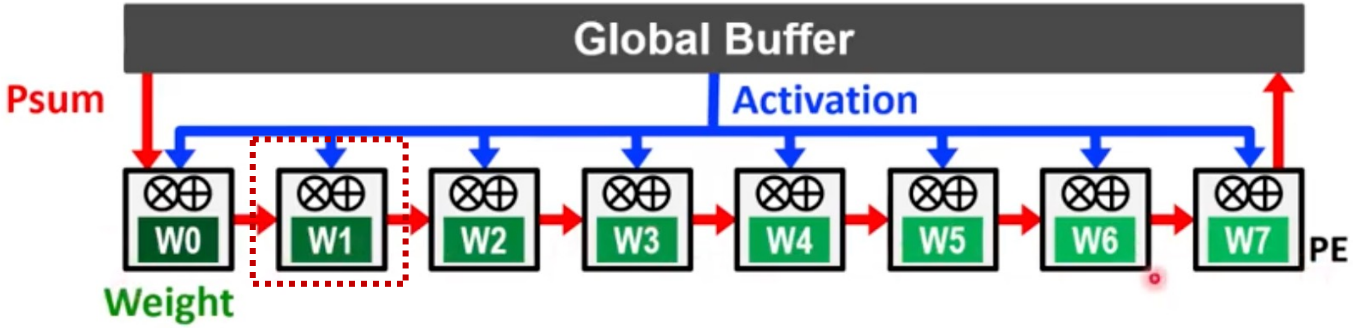


```python
def mac_worker(weight, input_queue,
               left_partial_sum_queue, right_partial_sum_queue):
```

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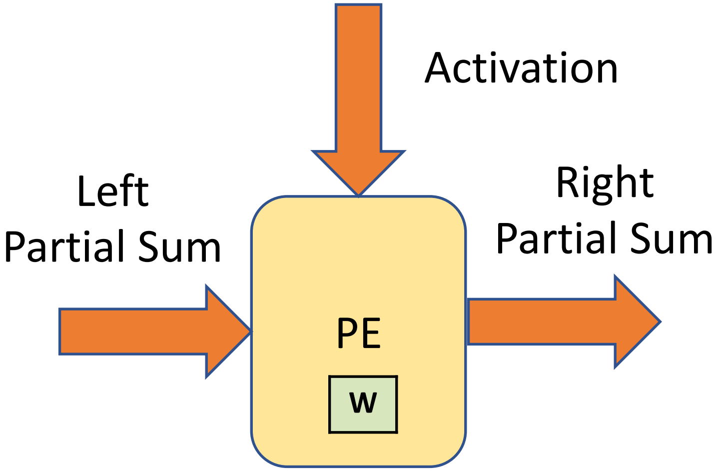

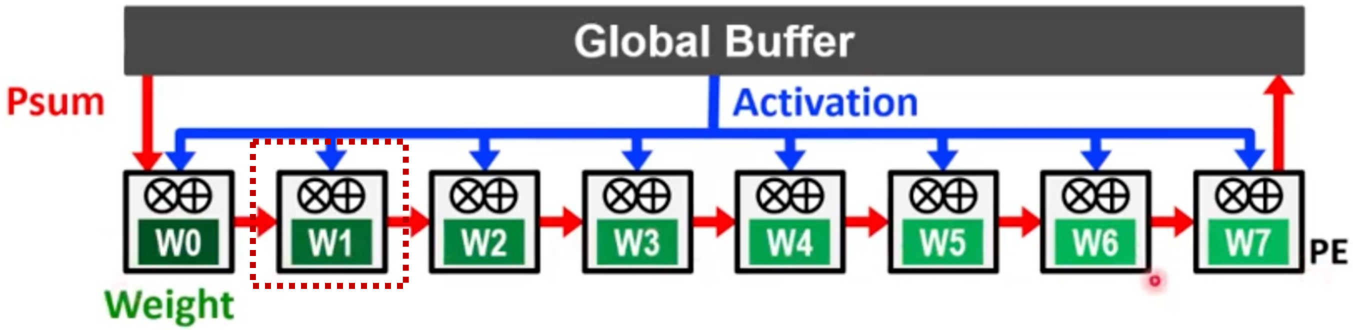


```python
def mac_worker(weight, input_queue,
               left_partial_sum_queue, right_partial_sum_queue):

    while True:
```

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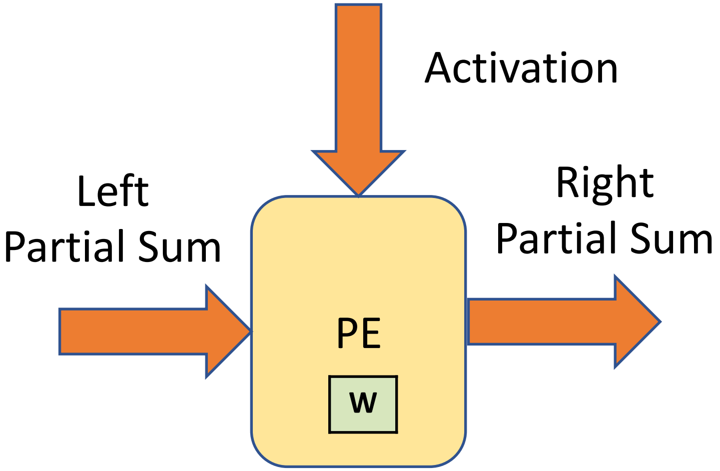

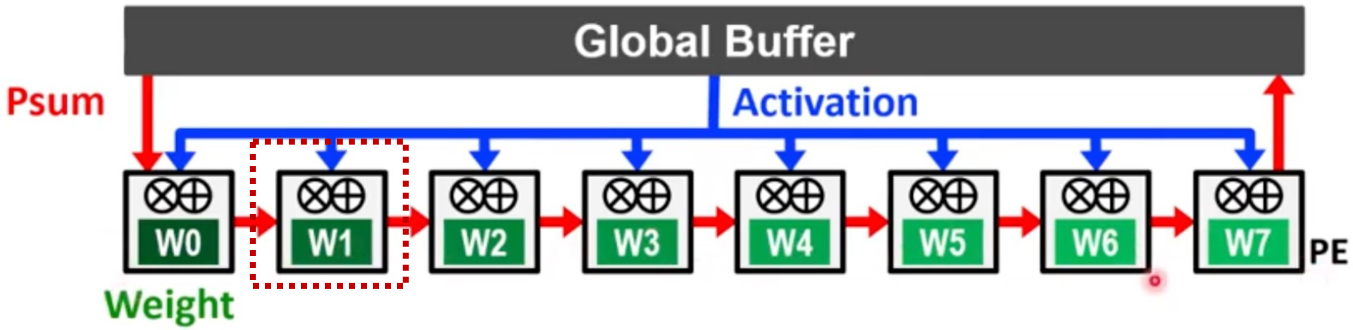


```python
def mac_worker(weight, input_queue,
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    while True:
        activation = input_queue.get()
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```

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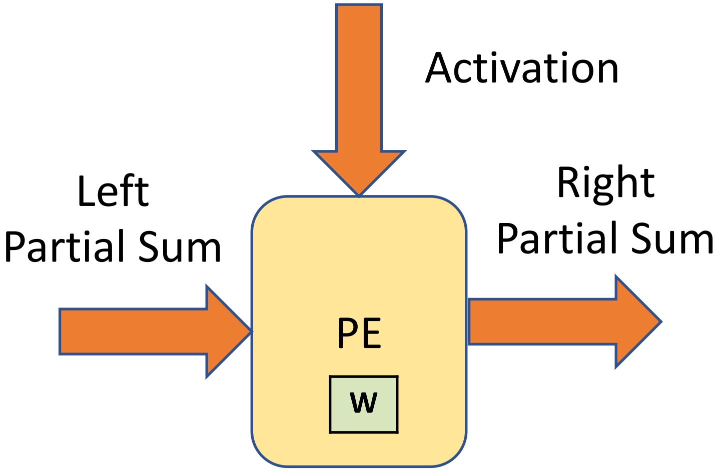

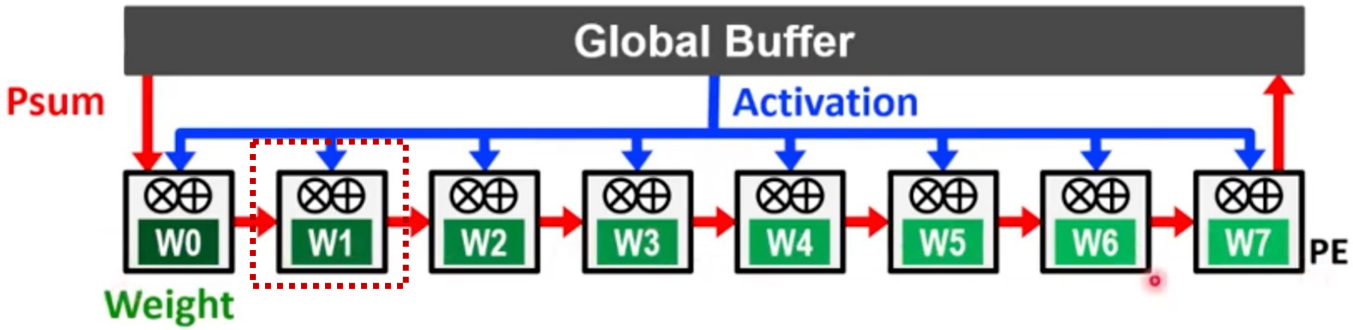


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        left_partial_sum = left_partial_sum_queue.get()
```

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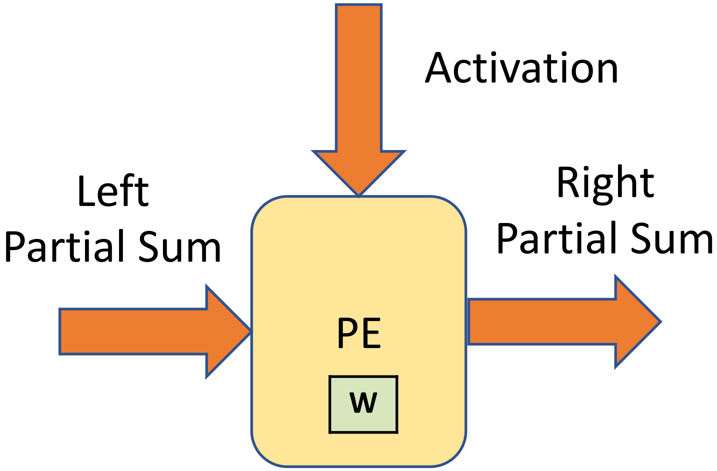
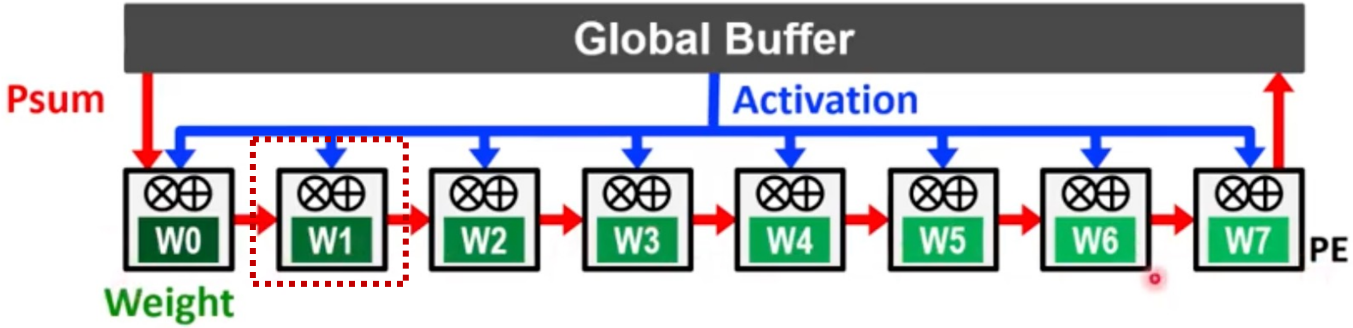


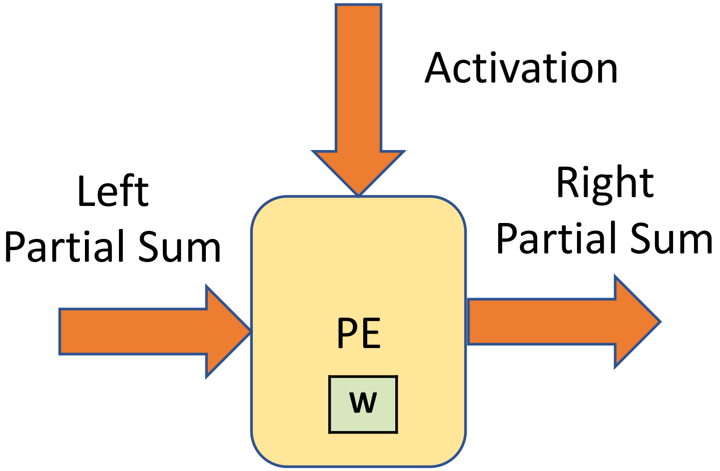


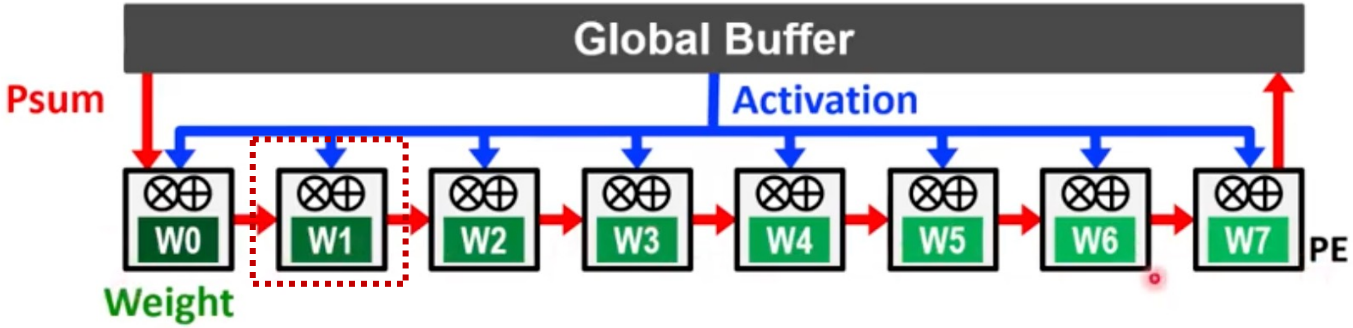

```python
def mac_worker(weight, input_queue,
               left_partial_sum_queue, right_partial_sum_queue):

    while True:
        activation = input_queue.get()
        if activation is None:
                break
        left_partial_sum = left_partial_sum_queue.get()

        right_partial_sum = left_partial_sum + activation * weight
```

What Does Each PE Do?





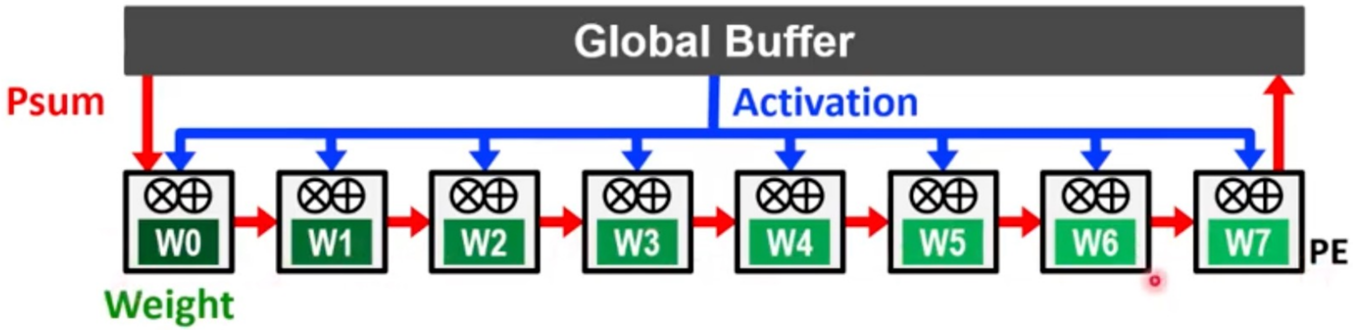

```python
def mac_worker(weight, input_queue,
               left_partial_sum_queue, right_partial_sum_queue):

    while True:
        activation = input_queue.get()
        if activation is None:
                break
        left_partial_sum = left_partial_sum_queue.get()

        right_partial_sum = left_partial_sum + activation * weight

        right_partial_sum_queue.put(right_partial_sum)
```

What Does Each PE Do?




```
num_workers = 8
weights = [1.0 * i for i in range(num_workers)] # Example weights

input_queues = [Queue() for _ in range(num_workers)]
partial_sum_queues = [Queue() for _ in range(num_workers + 1)] # Extra one for the initial input

# Initialize the leftmost partial sum queue
partial_sum_queues[0].put(0) # Initial partial sum


# Instantiate and start workers
workers = []
for i in range(num_workers):
        w = Process(target=mac_worker, args=(
        weights[i], input_queues[i], partial_sum_queues[i], partial_sum_queues[i+1]))
        workers.append(w)
        w.start()
```

Synchronous SystemVerilog Model

- Our Abstract Python models are asynchronous for simplicity.
- In practice PEs are commonly implemented synchronously using a clock signal

```
module MacWorker (
  input wire clk,
  input wire reset,
  input wire [31:0] activation, // Activation input
  input wire [31:0] weight, // Weight (stationary)
  input wire [31:0] left_partial_sum_signal, // Incoming partial sum
  output reg [31:0] right_partial_sum_signal // Output partial sum
);
  reg [31:0] left_partial_sum; // Stored partial sum (weight-stationary)

  always @(posedge clk or posedge reset) begin
    if (reset) begin
      left_partial_sum <= 0;
      right_partial_sum_signal <= 0;
    end else begin
      left_partial_sum <= left_partial_sum_signal;
      right_partial_sum_signal <= left_partial_sum
                 + (activation * weight);
    end
  end
endmodule
```

Synchronous SystemC Model

- For high level modeling, SystemC can be used.
- Use SystemC if:
  - You need high-level system modeling (e.g., processor simulation, transaction-level modeling).
  - You want to write HLS-based designs (C++ → Verilog).
  - You are working on algorithm validation before RTL implementation.

```
#include <systemc.h>

SC_MODULE(MacWorker) {
  // Ports
  sc_in<bool> clk;
  sc_in<bool> reset;
  sc_in<sc_int<32>> activation; // Activation input
  sc_in<sc_int<32>> weight; // Stationary weight input
  sc_in<sc_int<32>> left_partial_sum_signal; // Incoming partial sum
  sc_out<sc_int<32>> right_partial_sum_signal; // Output partial sum
  // Internal register for pipeline efficiency
  sc_signal<sc_int<32>> left_partial_sum;

  // MAC process
  void mac_process() {
    if (reset.read() == 1) {
      left_partial_sum.write(0);
      right_partial_sum_signal.write(0);
    } else {
      // Store the left partial sum (stabilizing input)
      left_partial_sum.write(left_partial_sum_signal.read());

      // Perform MAC operation
      right_partial_sum_signal.write(left_partial_sum.read() +
              (activation.read() * weight.read()));
    }
  }

  // Constructor
  SC_CTOR(MacWorker) {
  SC_METHOD(mac_process);
  sensitive << clk.pos(); // Triggered on the positive clock edge
  sensitive << reset; // Also sensitive to reset
  }
};
```

Modeling in PyTorch or TensorFlow

```
import torch

activation = torch.tensor(3, dtype=torch.int32)
weight = torch.tensor(2, dtype=torch.int32) # Stationary weight
left_partial_sum = torch.tensor(5, dtype=torch.int32)

# Compute MAC operation
right_partial_sum = left_partial_sum + (activation * weight)

print("Right Partial Sum (PyTorch):", right_partial_sum.item())
```

Best for **research, flexible ML models, and GPU execution**

```
import tensorflow as tf

# Define input tensors
activation = tf.constant(3, dtype=tf.int32)
weight = tf.constant(2, dtype=tf.int32) # Stationary weight
left_partial_sum = tf.constant(5, dtype=tf.int32)

# Compute Right Partial Sum
right_partial_sum = left_partial_sum + (activation * weight)

# Run in TensorFlow
print("Right Partial Sum:", right_partial_sum.numpy())
```

Best for **training and deploying models on GPUs/TPUs**.

Note that these are used for mapping to existing hardware

Modeling in TVM

- **High-Level ML Model**
  - TVM takes models from **TensorFlow, PyTorch, ONNX, etc.**
  - Converts them into **Relay IR** (Intermediate Representation).
- **Optimizations and Lowering**
  - TVM applies **auto-scheduling, memory layout transformations, loop optimizations**.
  - Lowers computations to **hardware-specific backends**.
- **Generates Target-Specific Code**
  - **For CPUs → LLVM IR** (Compiles to assembly/machine code).
  - **For NVIDIA GPUs → CUDA** (Optimized for tensor cores).
  - **For FPGAs → OpenCL / HLS C++** (Can be synthesized into Verilog/VHDL).
  - **For Custom ASICs → Maps to low-level tensor instructions** (But does not generate Verilog directly).

```python
import tvm
from tvm import te
import numpy as np

A = te.var("A") # Activation
W = te.var("W") # Stationary weight
L = te.var("L") # Left partial sum

# Compute Right Partial Sum
Right_Partial_Sum = te.compute(
(1,), lambda i: L + (A * W), name="Right_Partial_Sum"
)

# Create a schedule
s = te.create_schedule(Right_Partial_Sum.op)

# Compile for CPU (Can change to CUDA for GPU or FPGA backend)
target = "llvm"
f = tvm.build(s, [A, W, L, Right_Partial_Sum], target=target)

# Run with sample values
ctx = tvm.cpu()
A_val = tvm.nd.array(np.array([3], dtype="int32"), ctx)
W_val = tvm.nd.array(np.array([2], dtype="int32"), ctx) # Stationary
L_val = tvm.nd.array(np.array([5], dtype="int32"), ctx)
R_out = tvm.nd.empty((1,), dtype="int32", ctx)

f(A_val, W_val, L_val, R_out)
print("Right Partial Sum (TVM):", R_out.asnumpy()[0])
```

TVM is mostly used for mapping to existing hardware, it does not replace SystemVerilog

Best for **optimizing ML models for custom hardware (FPGAs, TPUs, ASICs, Edge devices).**

TensorFlow vs. PyTorch vs. TVM

Feature	**TensorFlow**	**PyTorch**	**TVM**
Purpose	ML model definition & execution	ML model definition & execution	ML model compilation & optimization for hardware
Hardware Optimization	Uses **XLA** (Accelerates on CPU, GPU, TPU)	Uses **TorchScript** & ONNX for model optimization	Uses **Relay IR** to map models onto **CPU, GPU, FPGA, ASICs**
Custom Hardware Support	❌ No, limited to TensorFlow-supported hardware	❌ No direct hardware mapping, but can export to TVM	✅ Yes, supports custom **ASICs, FPGAs, TPUs**
Programming Model	High-level ML framework (Keras, TF functions)	High-level ML framework (Eager execution, TorchScript)	Low-level tensor scheduling and compilation
Fine-Grained Scheduling	❌ No	❌ No	✅ Yes, allows **custom scheduling for different hardware**
Deployment	Cloud (TPU), GPU, Edge (TF Lite)	Cloud (GPU, CPU), Edge (TorchScript)	Can optimize for **embedded devices, TPUs, GPUs, and FPGAs**
Example Use Case	Training & deploying ML models on **NVIDIA GPUs & TPUs**	Training & deploying ML models on **NVIDIA GPUs**	**Optimizing models for hardware accelerators (e.g., FPGAs, ASICs, Edge TPUs)**