An Introduction to Practical 2

Lecture 4 for Advanced Deep Learning Systems

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Introduction

Introduction

Two labs are in Practical 2

- Lab 3: A quantization search using MASE.
- Lab 4 (software stream): A toy Network Architecture Search (NAS) using MASE.
- Lab 4 (hardware stream): Writing and testing a fully-connected layer in SystemVerilog.

Deliverable

- A Markdown file: with all answers (plots, tables ...) of the questions and optional questions.
- Corresponding code in your forked repository.

Examination (15%)

- Submission requires the Markdown files only.
- Lab oral to check on your code and Q&A.

Lab 3: A quantization search using MASE

Problem setup

We allow multi-precision, this means different layers can use a different precision setup. This is also know mixed-quantization.

We would like to have at most $X\%$ accuracy degradation, and focus on quantizing the computationally heavy layers (eg. linear, convolution).

- If the network has N layers.
- Each layer has M quantization choices.
- N^M search space.

Classic Approach

```
1  class JSC_Tiny(nn.Module):
2      def __init__(self, info, qparam):
3          super(JSC_Tiny, self).__init__()
4          self.seq_blocks = nn.Sequential(
5              # 1st LogicNets Layer
6              nn.BatchNorm1d(16),  #  batch norm layer
7              QuantizedLinear(16, 5, qparam),  # linear layer
8          )
9
10     def forward(self, x):
11         return self.seq_blocks(x)
12 ...
13 for qparam in search_space:
14   evaluate(model(info, qparam))
15   ...
```

MASE

The classic method is not very scalable because it interleaves network definitions with the quantization optimization, what if

- We have a new network
- Or we have a new optimization
- Or we want to use this optimization in conjunction with other optimizations

```
for i, config in enumerate(search_spaces):
  mg = quantize_transform_pass(ori_mg, config)
  evaluate(mg)
```

MASEGraph Analysis Passes

```
1 mg = init_metadata_analysis_pass(mg, None)
2 mg = add_common_metadata_analysis_pass(mg, {"dummy_in":
  ↪  dummy_in})
3 mg = add_software_metadata_analysis_pass(mg, None)
```

'add_common_metadata_analysis_pass' uses the dummy input.

We have explained before that the fx_graph is a skeleton, it records minimal information, so how do we actually fetch input and model information from this skeleton to run an actual inference?

Analysis Pass Deepdive

The MaseGraph implementation largely relies on the torch fx_graphs.

When traversing an fx_graph, you actually need two components, that are the MASEGraph.fx_graph itself and MASEGraph.modules. One can imagine the fx_graph is a skeleton, it records minimal information.

- node.op
- node.target
- node.name
- node.args
- node.kwargs

The placeholder op

node.op is "placeholder"

- node.name is set to the variable name for the input
- node.target not used
- node.args not used
- node.kwargs not used

The call_function and call_module op

node.op is "call_function"

- node.name is function name
- node.target is the actual function
- node.args is the function arguments
- node.kwargs is the kwargs

node.op is "call_module"

- node.name is module name
- node.target is also the module name
- node.args is the function arguments
- node.kwargs is the kwargs

Tracing the information for these ops

```
for node in graph.fx_graph.nodes:
  args, kwargs = None, None
  if node.op == "placeholder":
    result = dummy_in[node.name]
  ...
  elif node.op == "call_function":
    args = load_arg(node.args, env)
    kwargs = load_arg(node.kwargs, env)
    result = node.target(*args, **kwargs)
  elif node.op == "call_module":
    args = load_arg(node.args, env)
    kwargs = load_arg(node.kwargs, env)
    result = graph.modules[node.target](*args, **kwargs)
  ...
```

Full code available in the implementation of add_common_metadata pass.

Lab 4 (software stream): A toy Network Architecture Search (NAS) using MASE

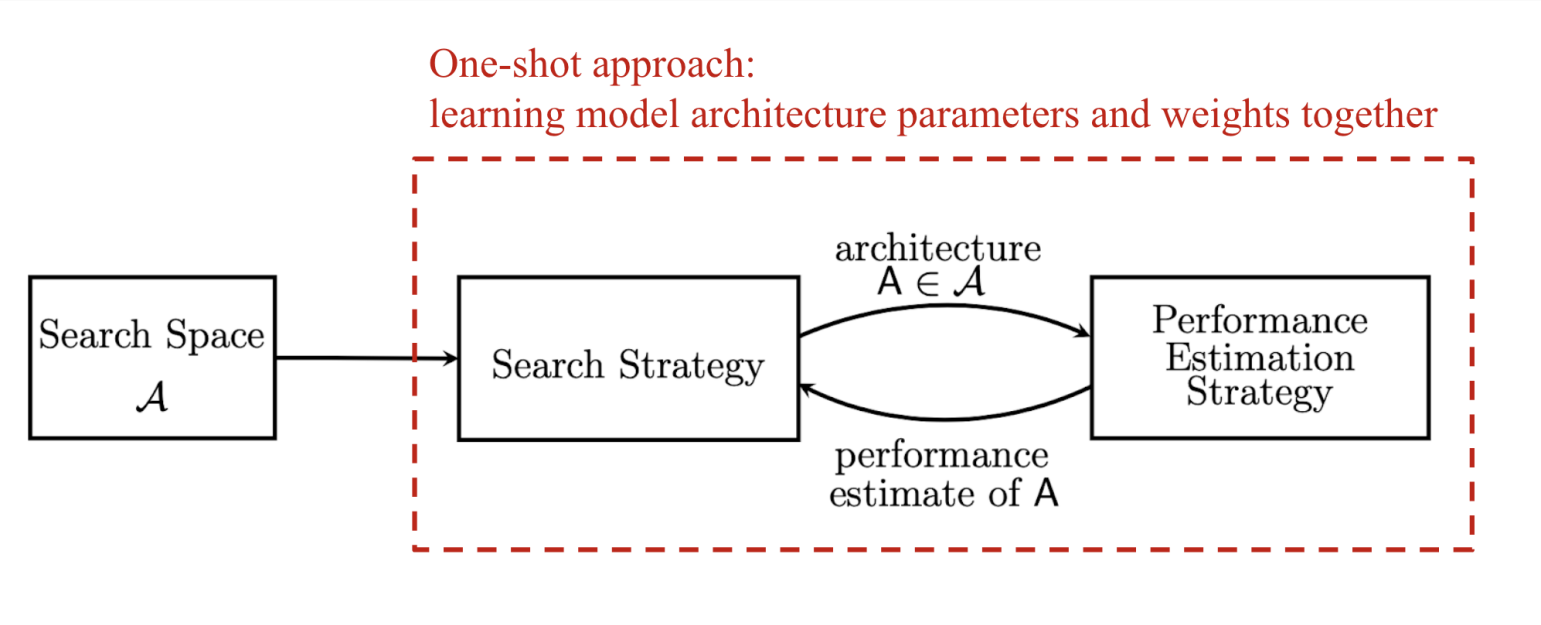
What is Network Architecture Search?

We want to pick the optimal architecture $a \in \mathcal{A}$ from a set of architectures $\mathcal{A}$.

At the same time, we want to pick the optimal parameters $w^*(a)$ for the architecture a.

$$\begin{aligned} & min_{a \in \mathcal{A}} \mathcal{L}_{val}(w^*(a), a) \\ & \quad s.t. w^*(a) = argmin_w(\mathcal{L}_{train}(w, a)) \end{aligned} \tag{1}$$

What is Network Architecture Search?



The idea of multiplied channels

```
1  class JSC_Three_Linear_Layers(nn.Module):
2    def __init__(self):
3      super(JSC_Three_Linear_Layers, self).__init__()
4      self.seq_blocks = nn.Sequential(
5          nn.BatchNorm1d(16),  # 0
6          nn.ReLU(16),  # 1
7          nn.Linear(16, 16),  # linear seq_2
8          nn.ReLU(16),  # 3
9          nn.Linear(16, 16),  # linear seq_4
10         nn.ReLU(16),  # 5
11         nn.Linear(16, 5),  # linear seq_6
12         nn.ReLU(5),  # 7
13     )
14
15   def forward(self, x):
16     return self.seq_blocks(x)
```

The idea of multiplied channels

```
class JSC_Three_Linear_Layers(nn.Module):
  def __init__(self):
      super(JSC_Three_Linear_Layers, self).__init__()
      self.seq_blocks = nn.Sequential(
          nn.BatchNorm1d(16),
          nn.ReLU(16),
          nn.Linear(16, 32),  # output scaled by 2
          nn.ReLU(32),  # scaled by 2
          nn.Linear(32, 64),  # input scaled by 2 but
          ↪  output scaled by 4
          nn.ReLU(64),  # scaled by 4
          nn.Linear(64, 5),  # scaled by 4
          nn.ReLU(5),
      )


  def forward(self, x):
      return self.seq_blocks(x)
```

The idea of multiplied channels

- The idea is to scale the input and output channels of the linear layer by a constant factor.
- In this lab, you will have to standardize this idea and implement it as a Transformation pass.
- Consecutive linear layers must be scaled by the same factor.
- Search through all the possible factors (brute force and Bayesian).

Lab 4 (hardware stream): Writing and testing a fully-connected layer in SystemVerilog

The goal of Lab4

Automatically generate a fully-connected layer in SystemVerilog, and test it using Cocotb.

Cocotb is a COroutine based COsimulation TestBench environment for verifying VHDL and SystemVerilog RTL using Python.

We use the Cocotb with Verilator backend.

Cocotb and Verilator

Cocotb: direct testing in Python, no need to write a testbench in SystemVerilog.

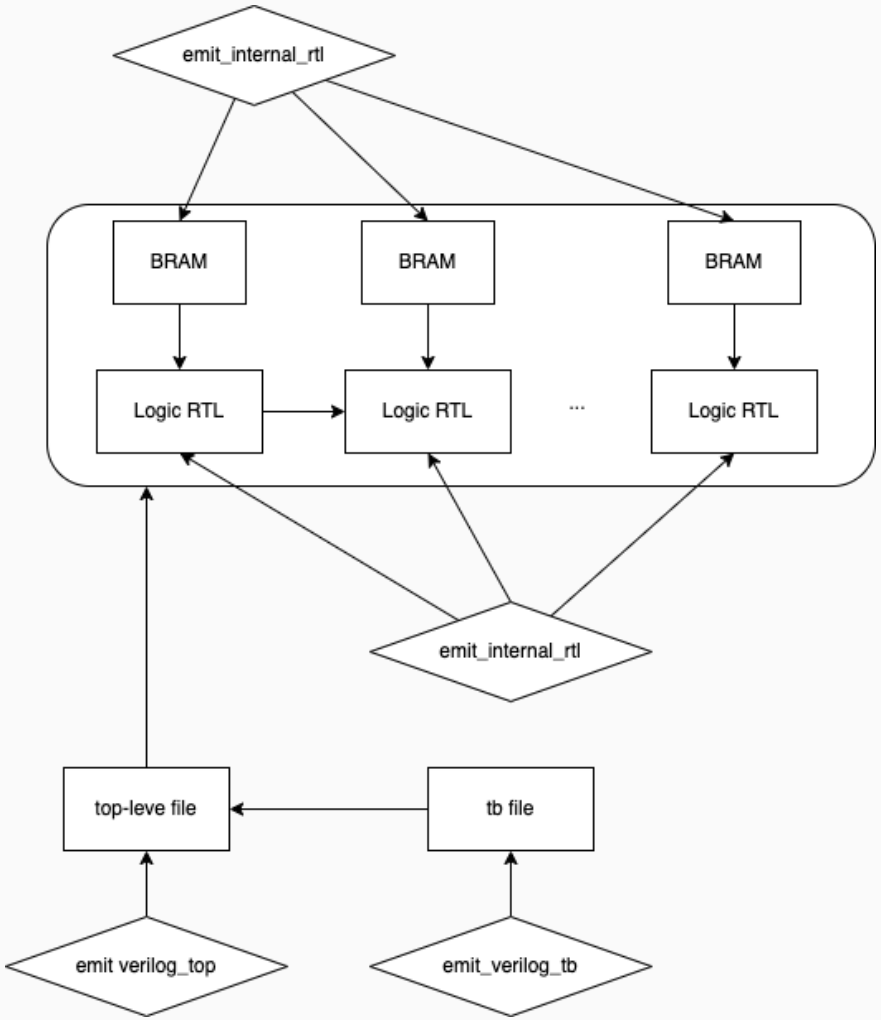
Verilator: 'up-compiles' SystemVerilog into multithreaded C++, lightening fast, no need to open vendor tools when doing behavior level testing.

EmitVerilog Pass in MASE

- Classic source to source generation
- Directly generate SystemVerilog from MaseGraph

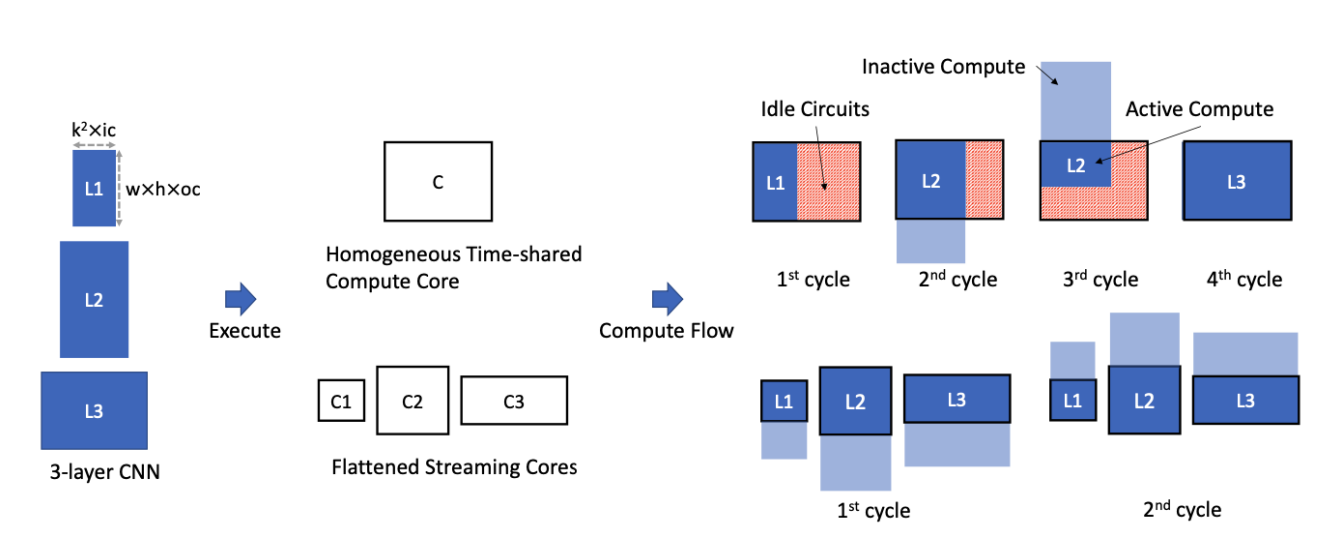
```
from chop.passes.graph.transforms import (
    emit_verilog_top_transform_pass,
    emit_internal_rtl_transform_pass,
    emit_bram_transform_pass,
    emit_verilog_tb_transform_pass,
)
```

EmitVerilog Pass in MASE



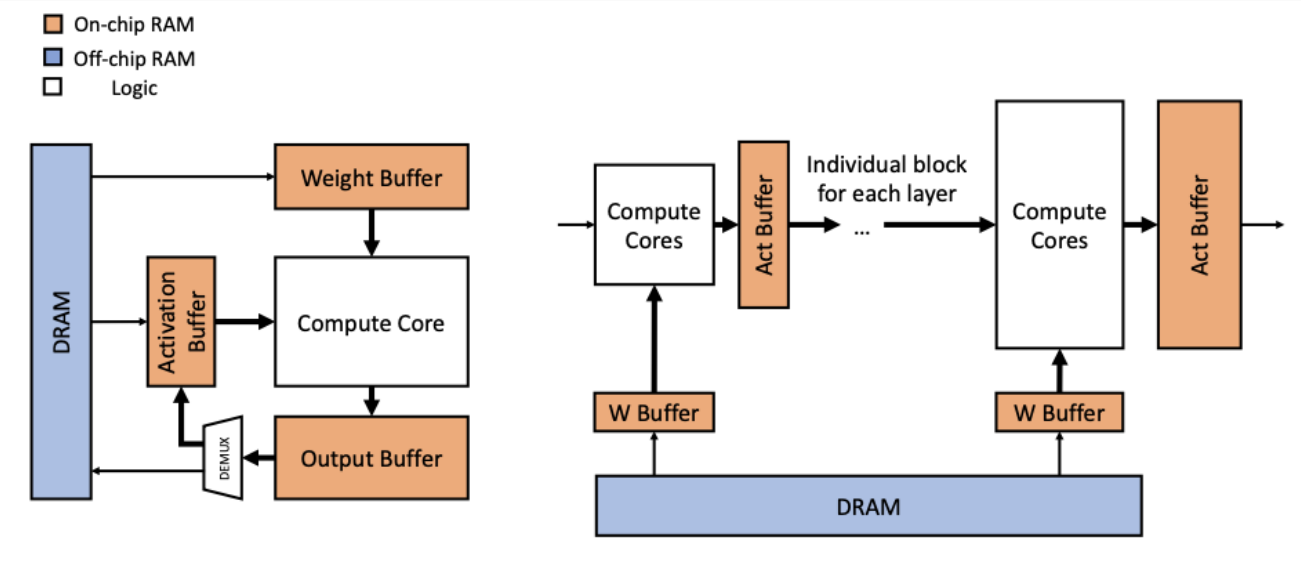
EmitVerilog generates dataflow designs

- Generate functional elements (RTL)
- Generate memory components (BRAM)
- Dataflow accelerator design without making use of the DRAM



Dataflow accelerator designs

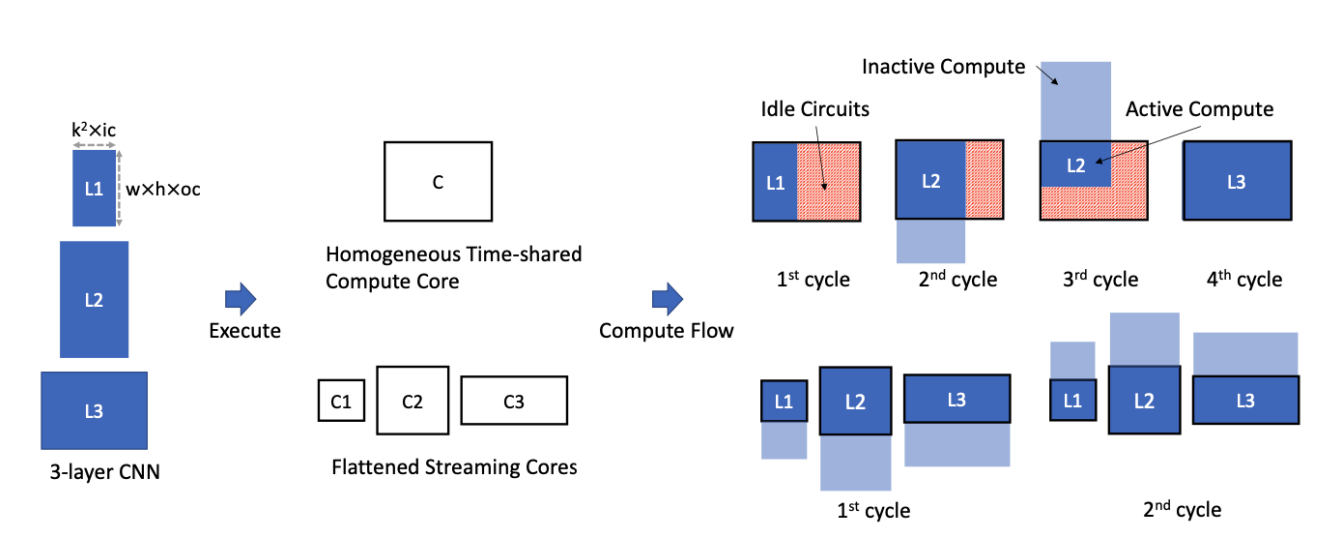
- A homogeneous Big Compute Core (normal design, ASIC)
- A series of tailored small compute cores (dataflow design, FPGA)



Dataflow accelerator design

Advantages

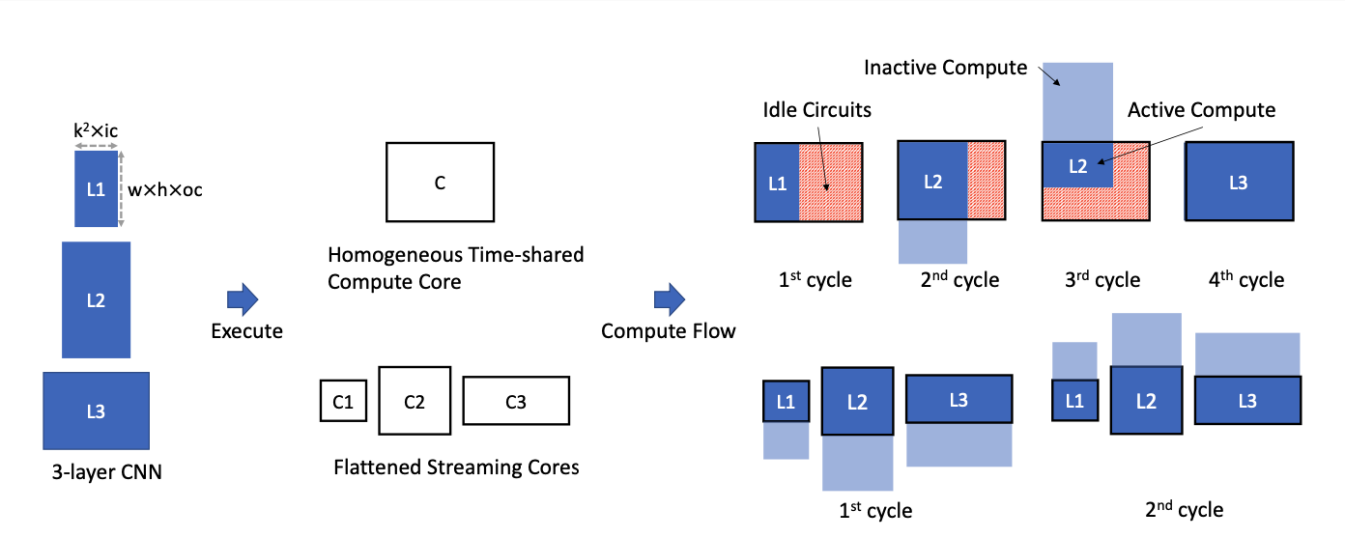
- No complex control flow (minimal or no ISA design)
- (Almost) no waste of resources
- (Almost) fixed memory access pattern
- Deep pipeline



Dataflow accelerator design

Disadvantages

- Re-program hardware for each new network
- Scalability issues
- If DRAM is utilized, hard to achieve great performance by filling up all pipeline stages

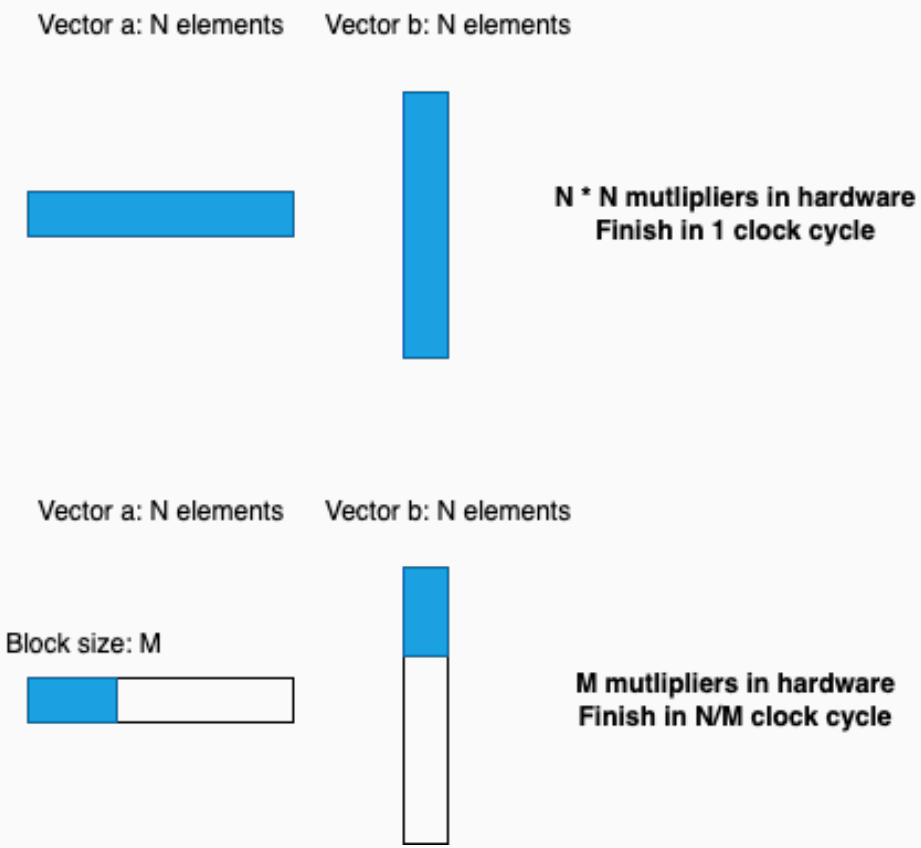


The compute pattern

Simple blocking

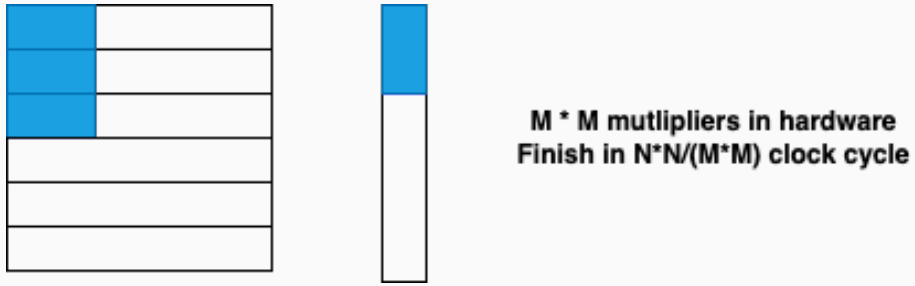
```
# Breaking the vector into blocks
for i in range(0, n, block_size):
    # calculate end val considering the last block which
    ↪  can be smaller than block_size
    end_val_i = min(i + block_size, n)

    # Retrieving block of a
    sub_a = a[i : end_val_i]
    # Retrieving corresponding elements from vector
    sub_b = b[i : end_val_i]

    # multiplication, actual hardware dimension is
    ↪  (block_size, 1)
    result += np.dot(sub_a, sub_b)
```

The compute pattern



- $N >> M$, this gives you a chance to do a trade-off between resources and latency simply by changing M.
- Blocking can happen in a 2D shape!

2D Blocking



- Parallel Multipliers (M^2).
- M Adder Trees ($log_2(M)$).
- M Accumulators (M).