Improving GPipe Partitioning

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Outline

- Project Introduction
- Technical Requirements
    - Timeline Profiling
    - Dynamic-Programming Partitioning
    - Throughput Estimation

Outline

- Experiments
  - Comparison with other Methods
  - Load Balancing
- Conclusion
  - Future Work
- References

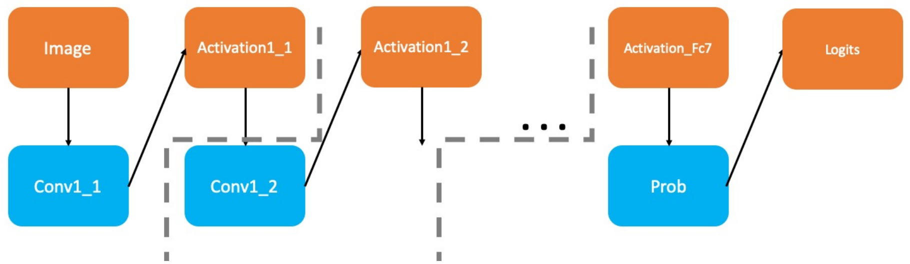
Project Introduction

Goal

- Facilitate GPipe parallel training process of giant neural networks to get better training throughput

Motivation

1. GPipe heuristic-based partitioning algorithm



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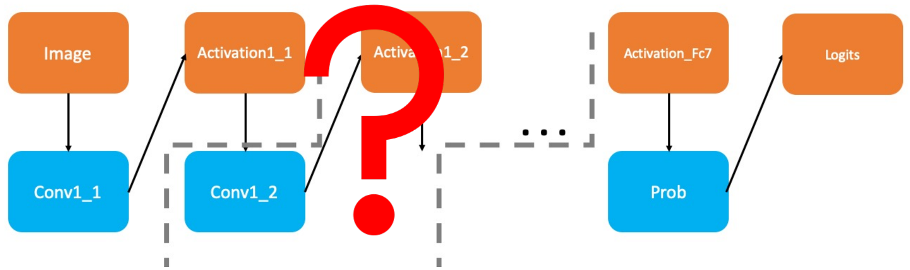

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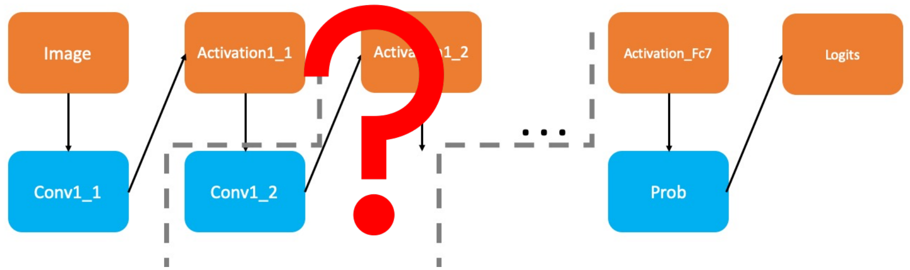

2. Imbalanced partition results in waiting time for next batch

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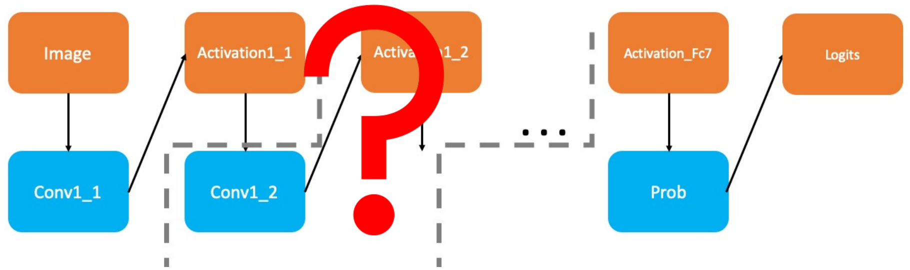

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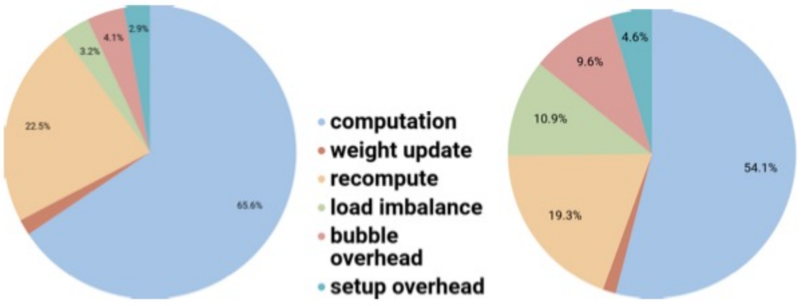

(a) Two Partitions
(b) Four Partitions

2 machines -> 4 machines
Overhead 3.2% -> 10.9%

Proposed Solution

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\+ PipeDream =

Proposed Solution – Black GPipe

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Proposed Solution – Black GPipe

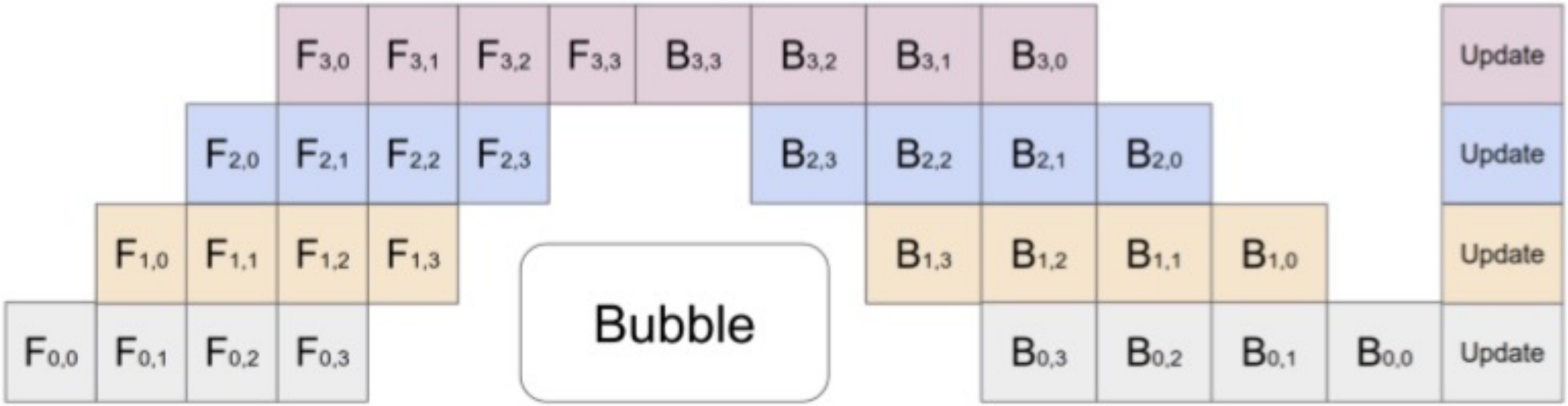
- Facilitate GPipe parallel training process of giant neural networks to get better training throughput
- To see if we can beat **DP** and **Naïve GPipe** on throughput

\+ PipeDream =

GPipe Micro-batch Recap

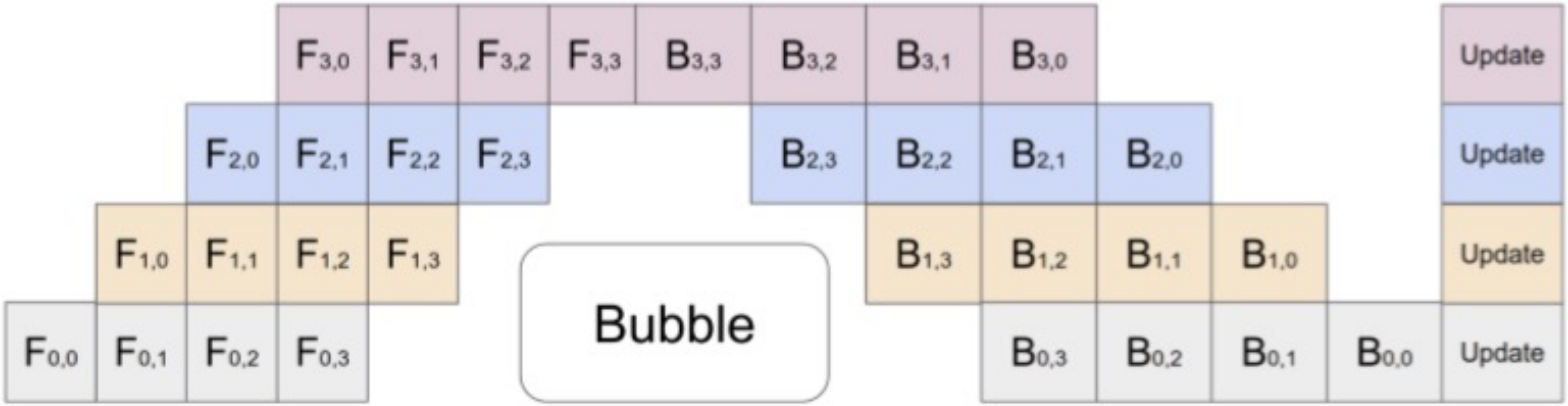
GPipe Micro-batch Recap

- Split mini-batch into several micro-batches



GPipe Micro-batch Recap

- We need time information for a micro-batch to estimate training time
- Execution time & Communication time



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1. Specify ***number of machines*** and ***number of micro-batches***
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Black GPipe Workflow

1. Specify ***number of machines*** and ***number of micro-batches***
   - Micro-batch size = Batch size / Number of micro-batches
2. Profile **Resnet-152** and **VGG19** to get time information w.r.t the micro-batch size
3. Use our algorithm to determine partition scheme (DP + MP)
4. For each stages, obtain its execution time and get the throughput of the model by estimation
   - Including backward and forward pass
   - Moreover in backward we implement re-computation

Timeline Profiling

Dynamic-Programming Partitioning

Throughput Estimation

What to Get?

- Profiles the DNN model with **micro-batch size $\boldsymbol{N/T}$**, and records
  - T_l: the total computation time across the forward pass for layer l
  - C_l: the communication time to send output from layer l and input to layer l+1
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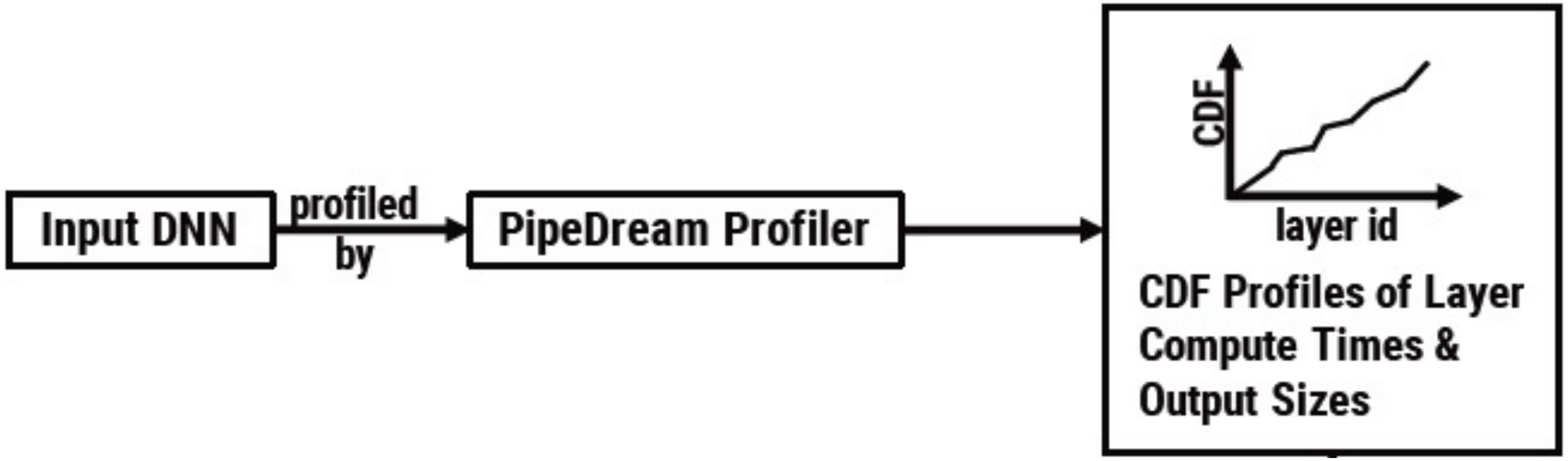
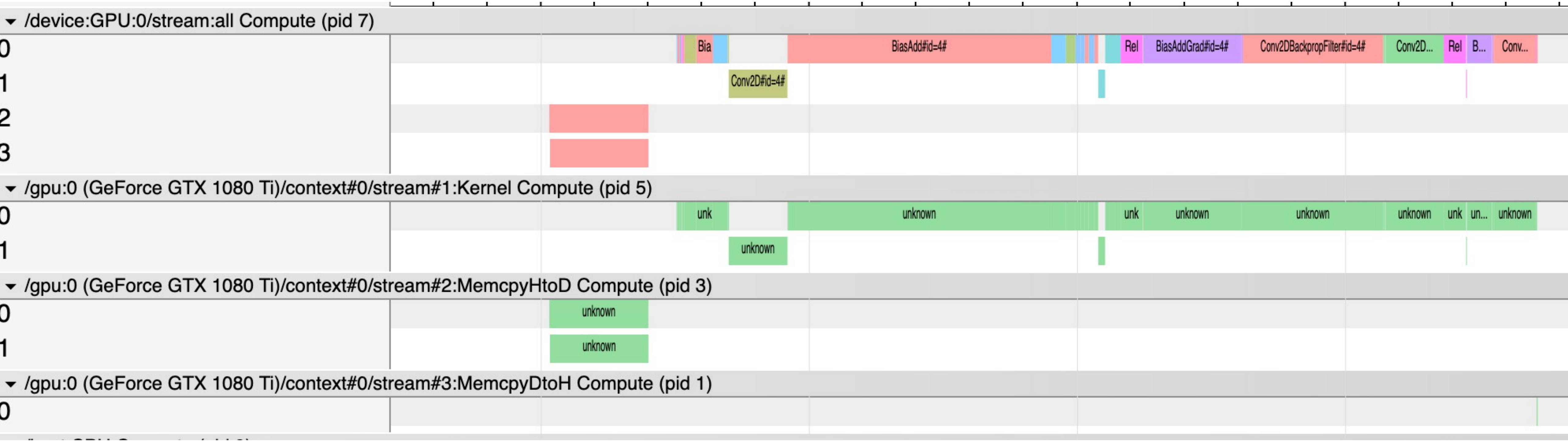


Fig. referred from [4].

How We Get?

- TensorFlow ***Timeline*** Object



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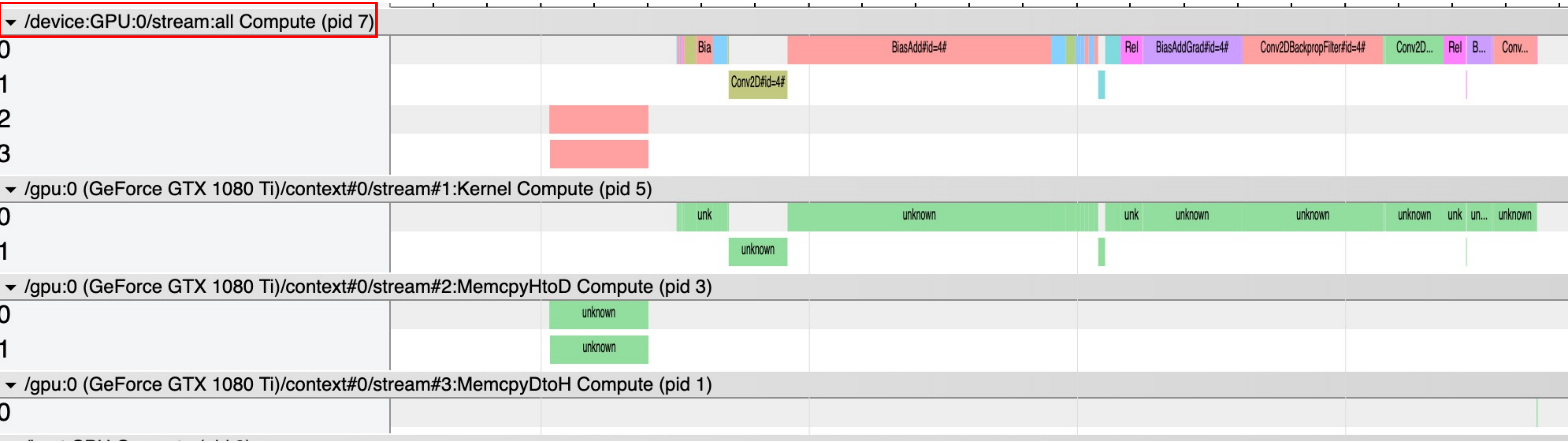

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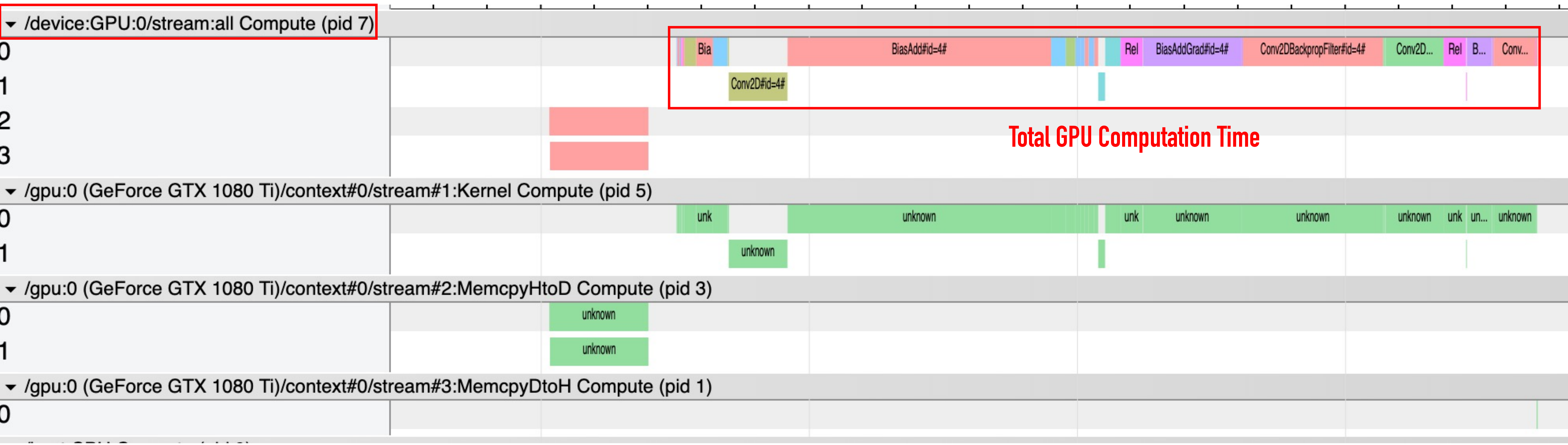

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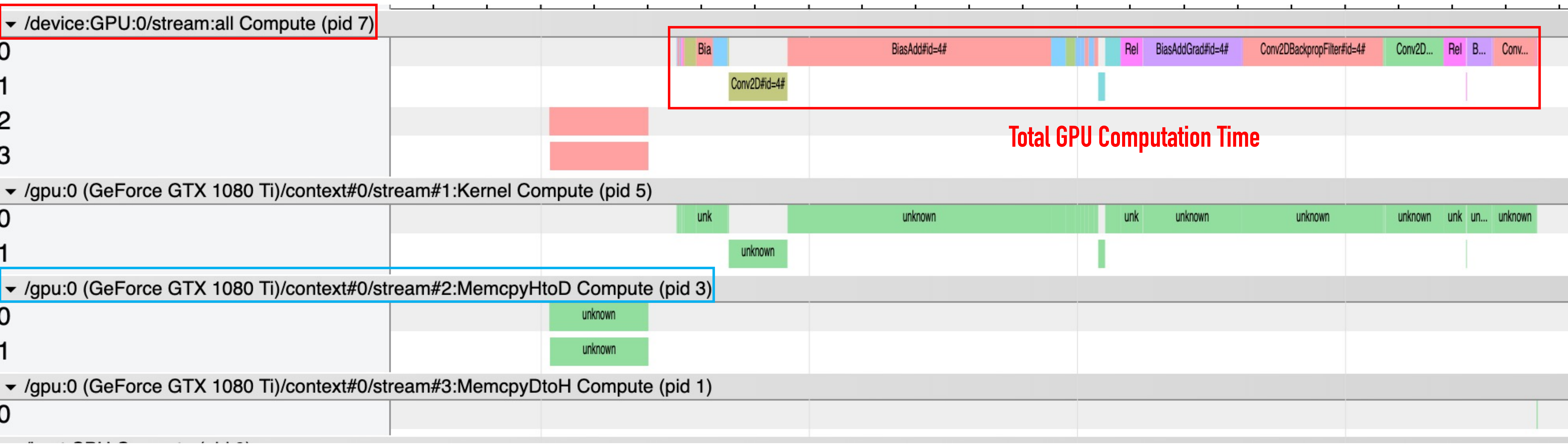

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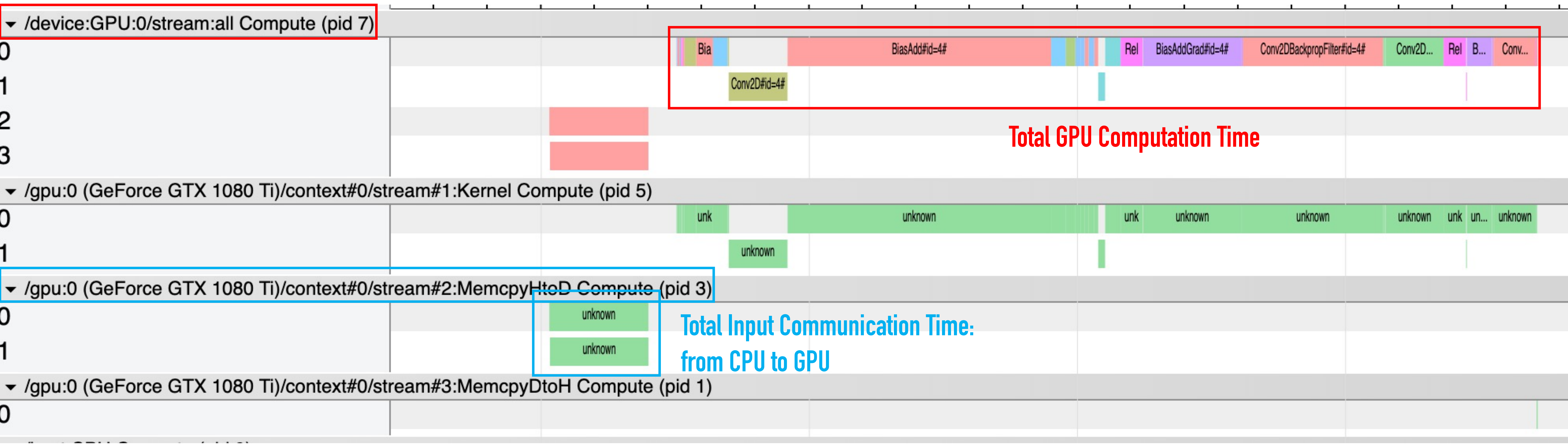

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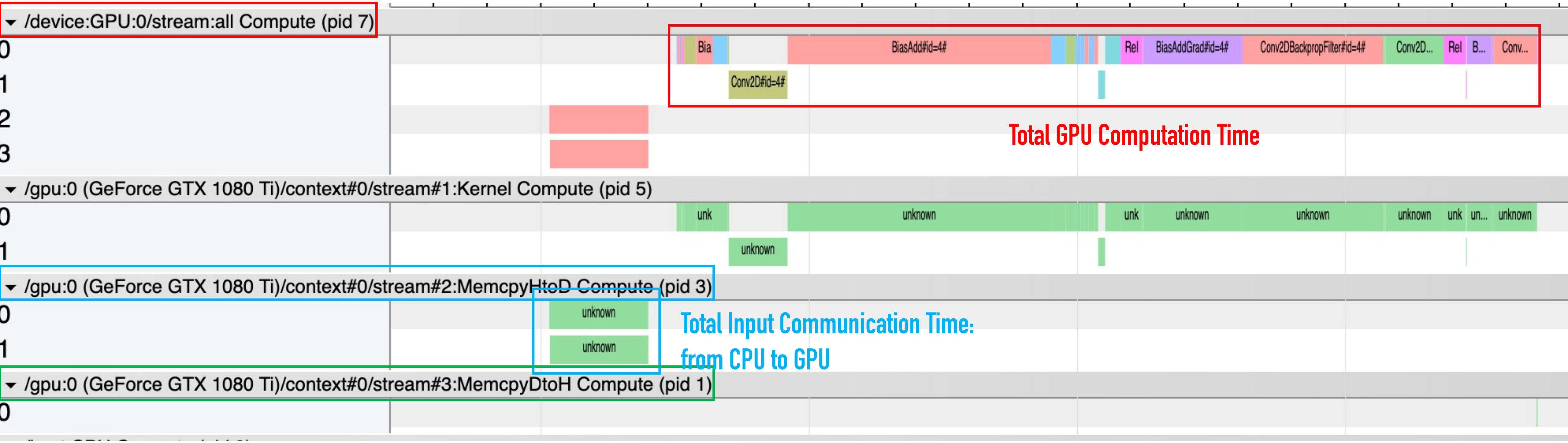

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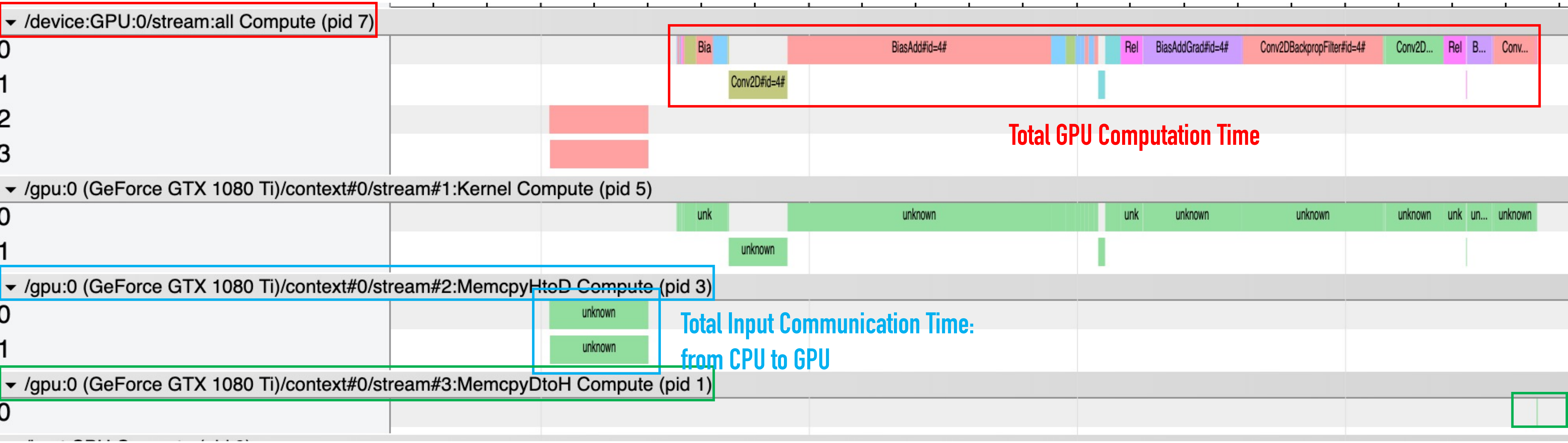

Total Output Communication Time :
from GPU to CPU

Why We Need This

Image

Let’s Look at A Model

- Assume no inter-connection between GPU
- Data Communication need to send between CPU and GPU

Image

Let's Look at A Model

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Image

CPU

GPU

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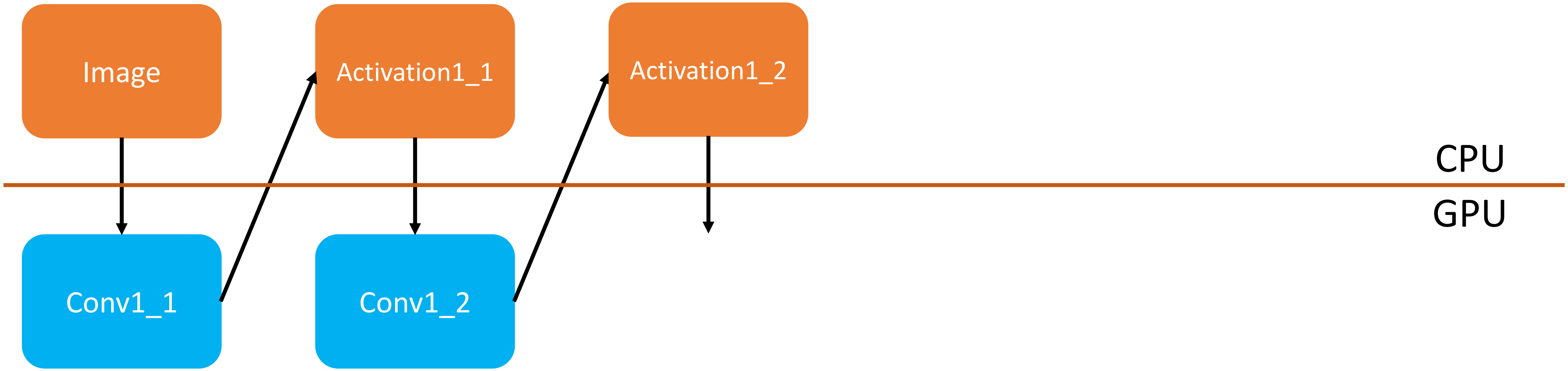

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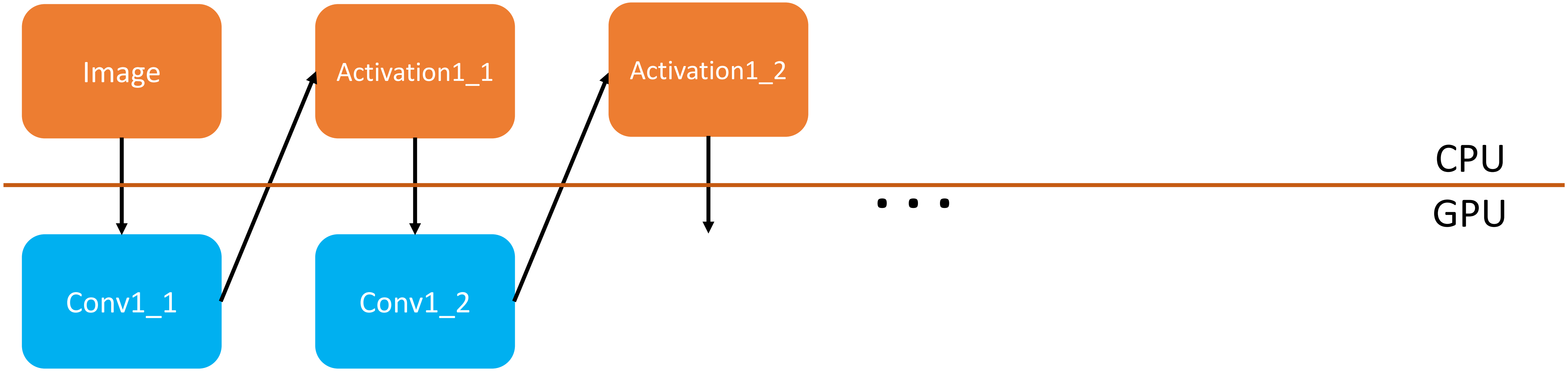

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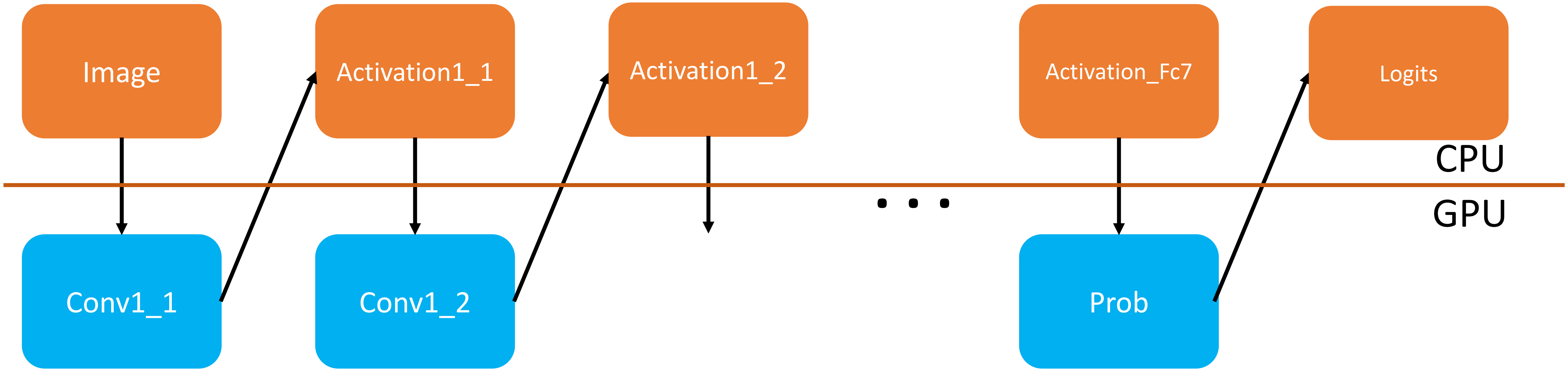
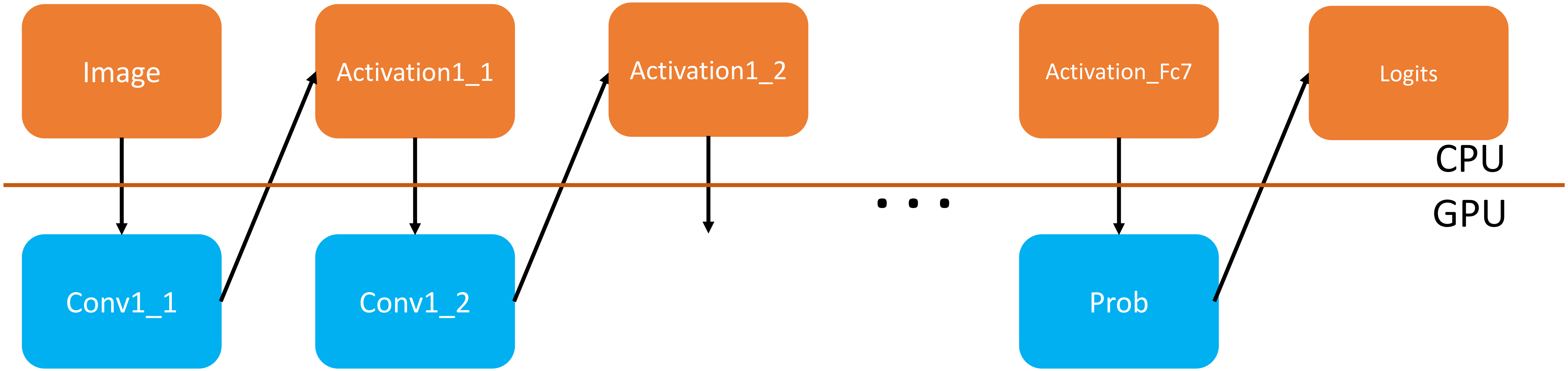


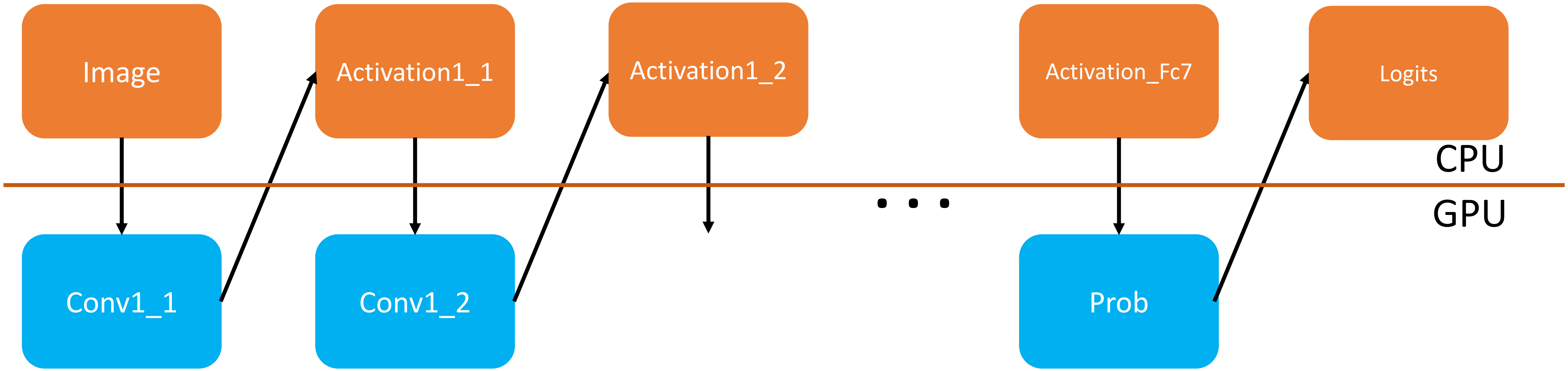
What We Want

- We need each layer's communication time which are
  - the time to send activations from GPU to CPU **w.r.t current layer**
  - and time to send these activations from CPU back to GPU **w.r.t next layer**

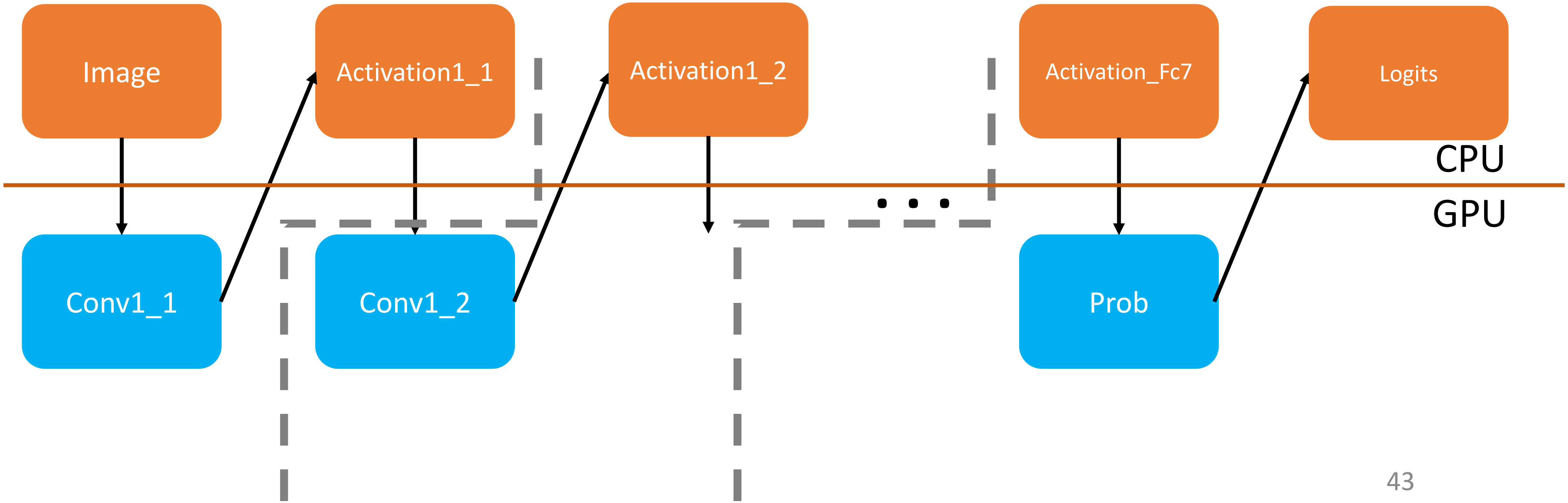


What We Want

- Since we want to find a split point to split model into stages
- We need this communication time to determine the cost of this split point

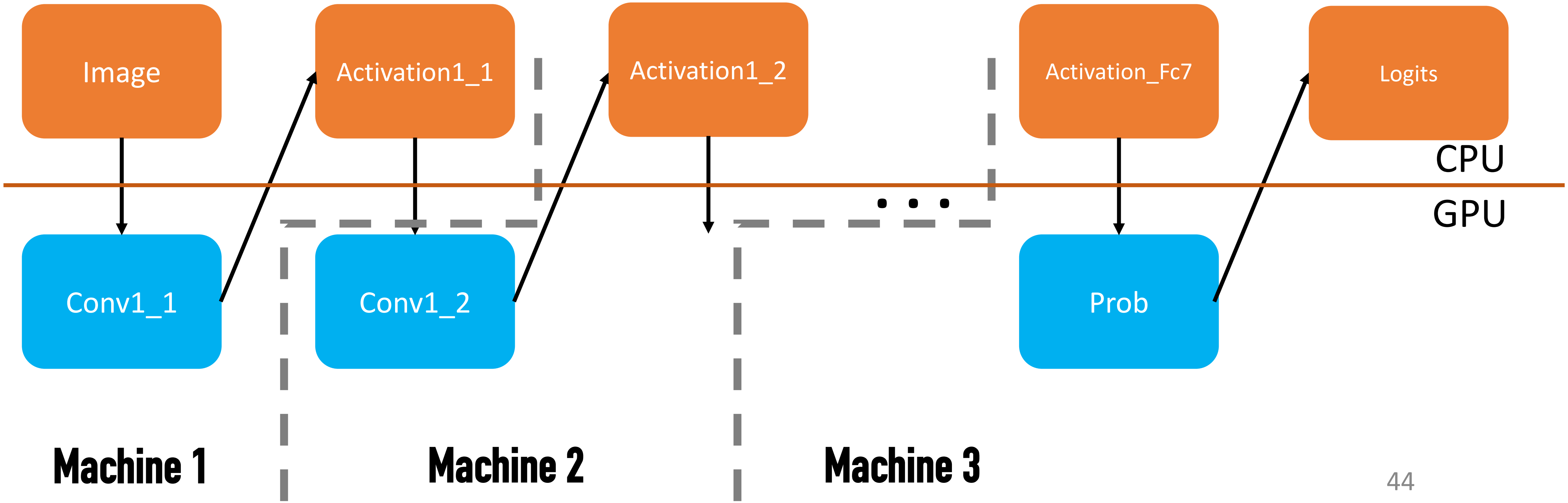


Split Model into Stages



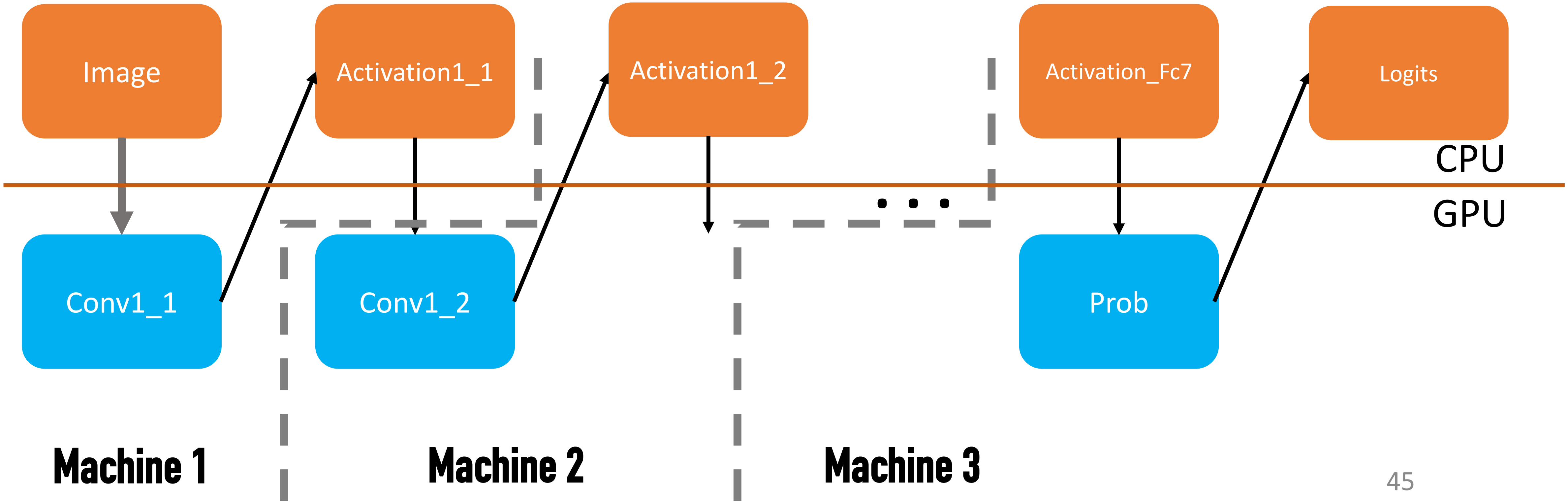
Split Model into Stages

- We have 3 machines computing this model

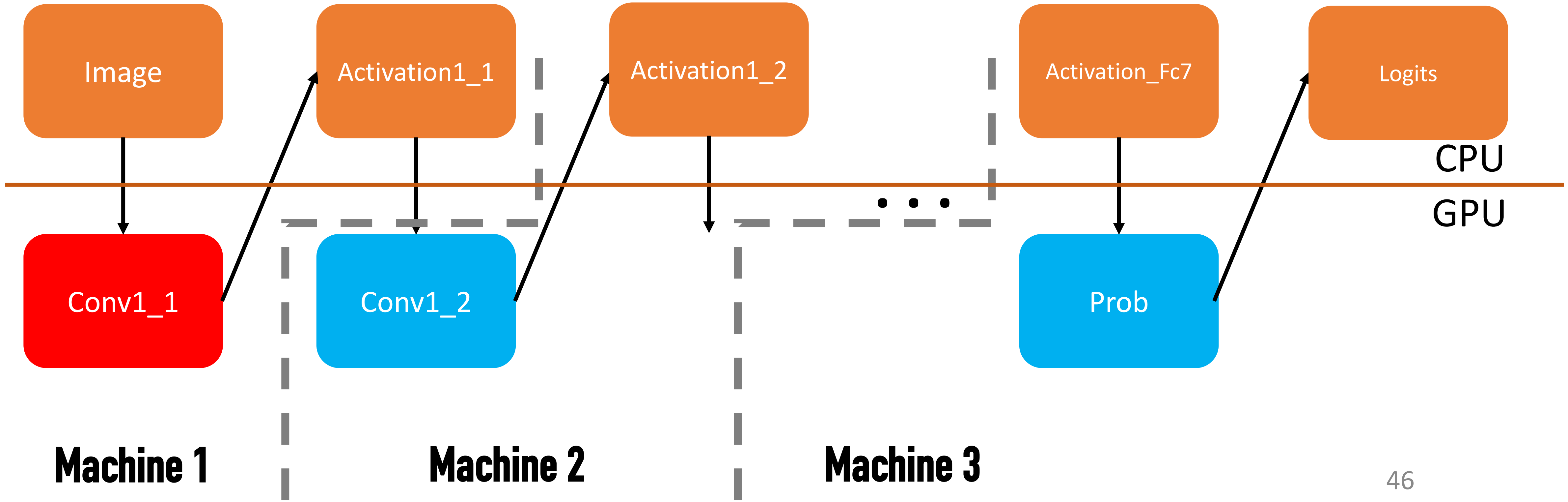


Dataflow Explain

- Input image communication (ignore this operation cost)

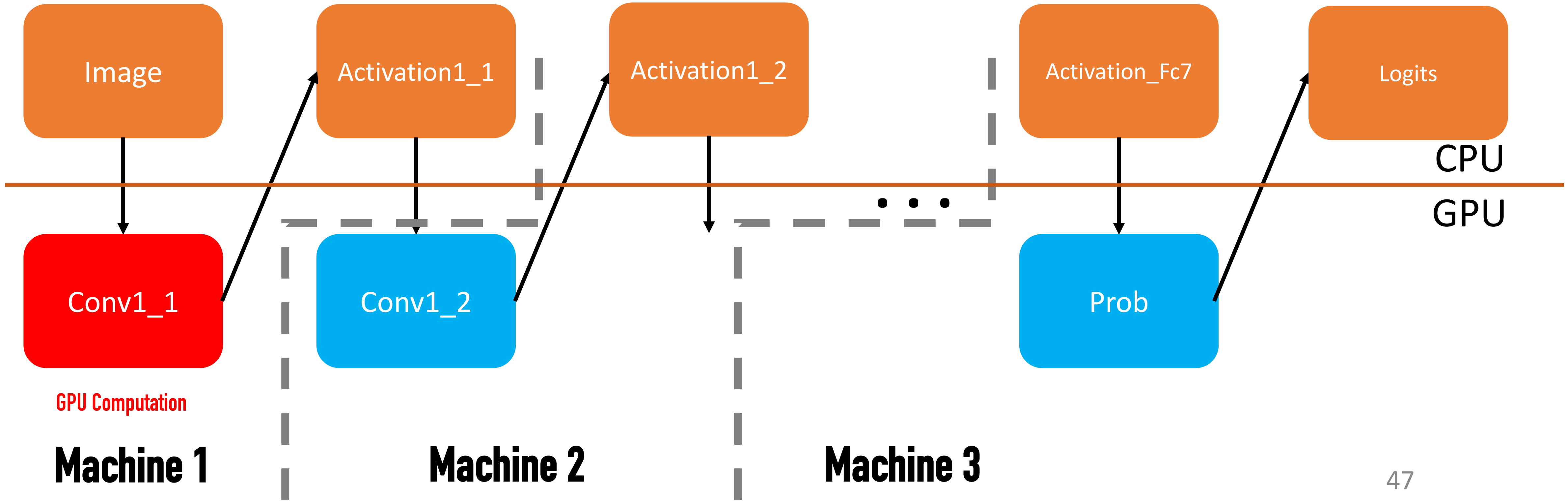


Dataflow Explain

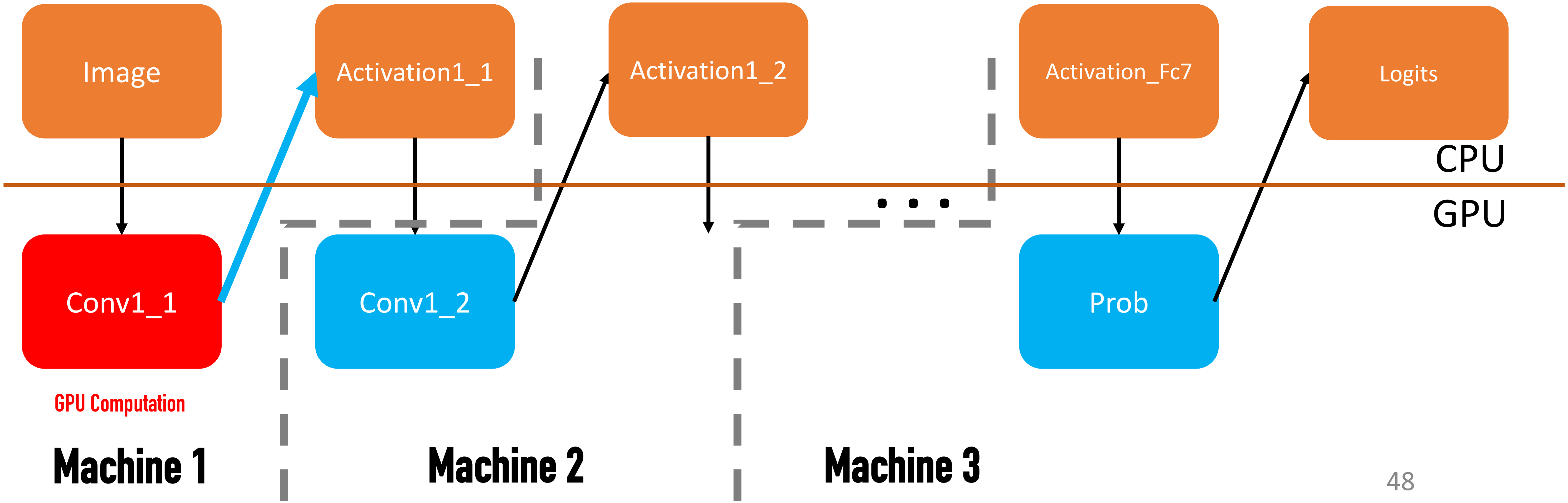


Dataflow Explain

- Layer Conv1_1 computation time

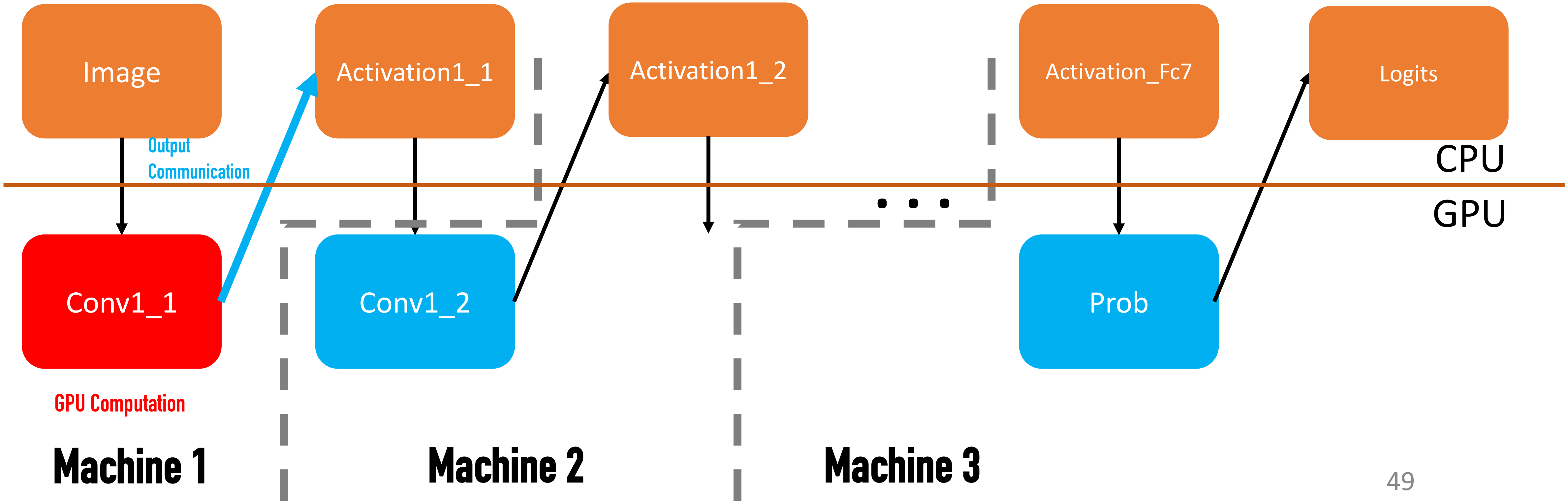


Dataflow Explain



Dataflow Explain

- Output activation of layer Conv1_1 communication time



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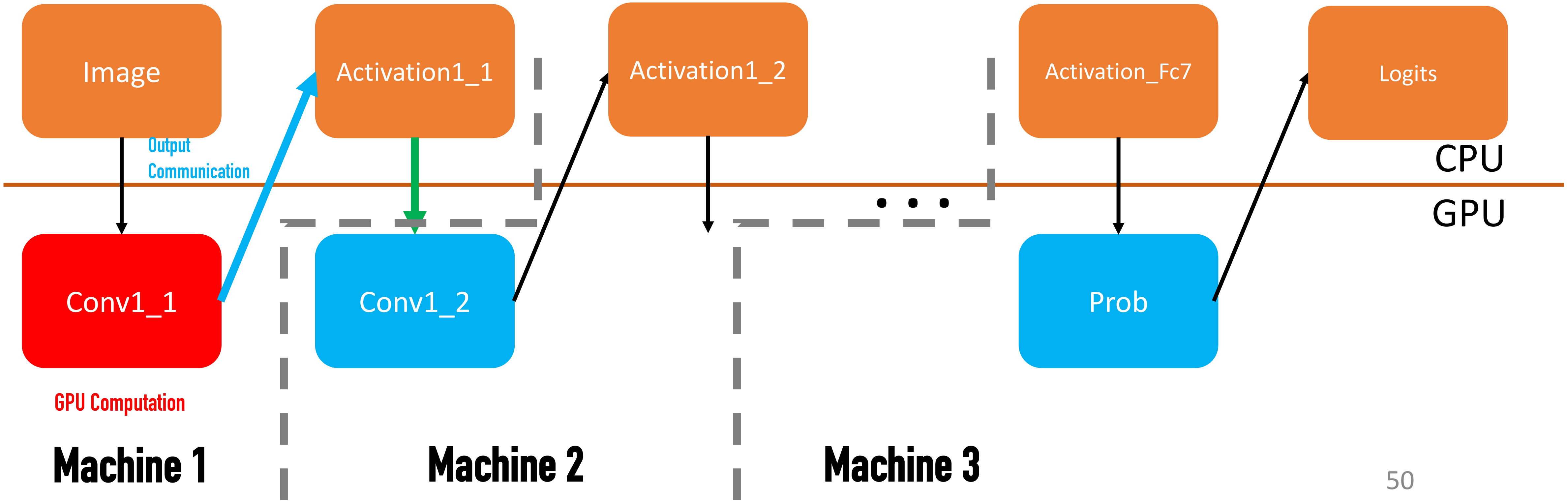
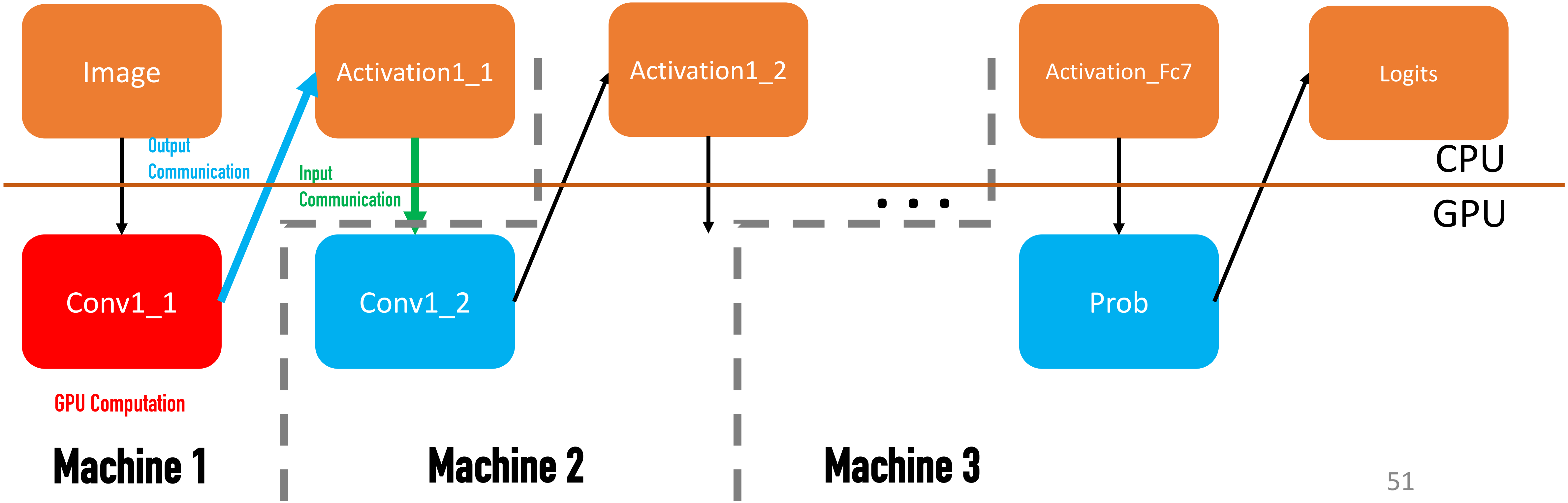


Dataflow Explain

- Output activation of layer Conv1_1 communication time
- Input activation of next layer Conv1_2 communication time



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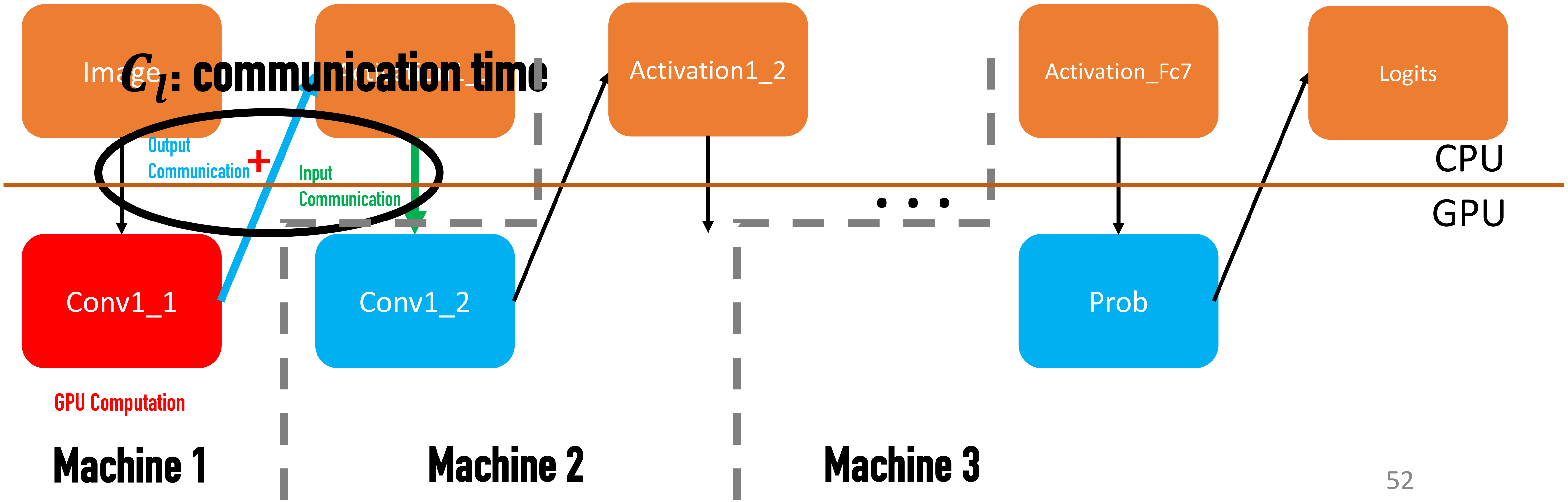

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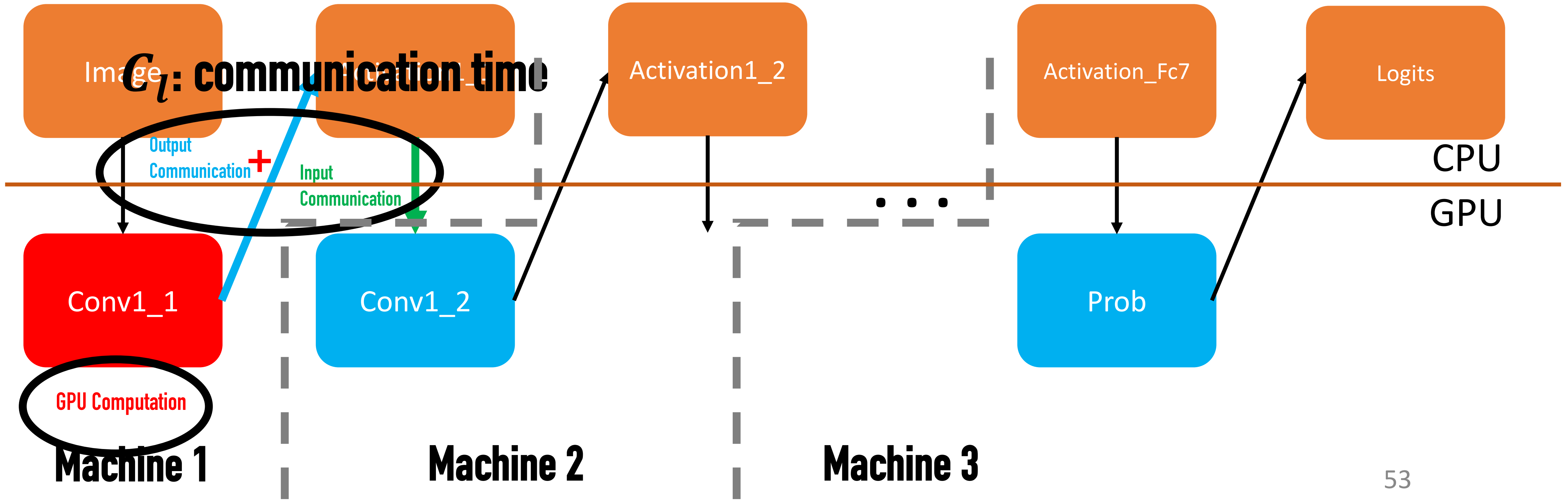

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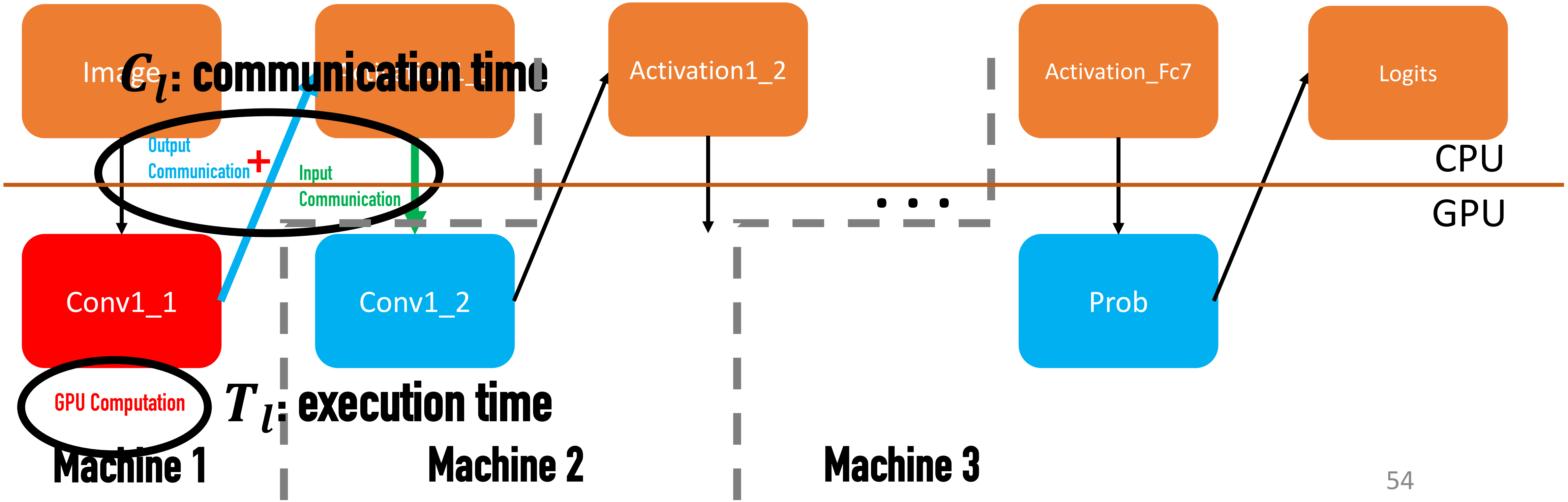
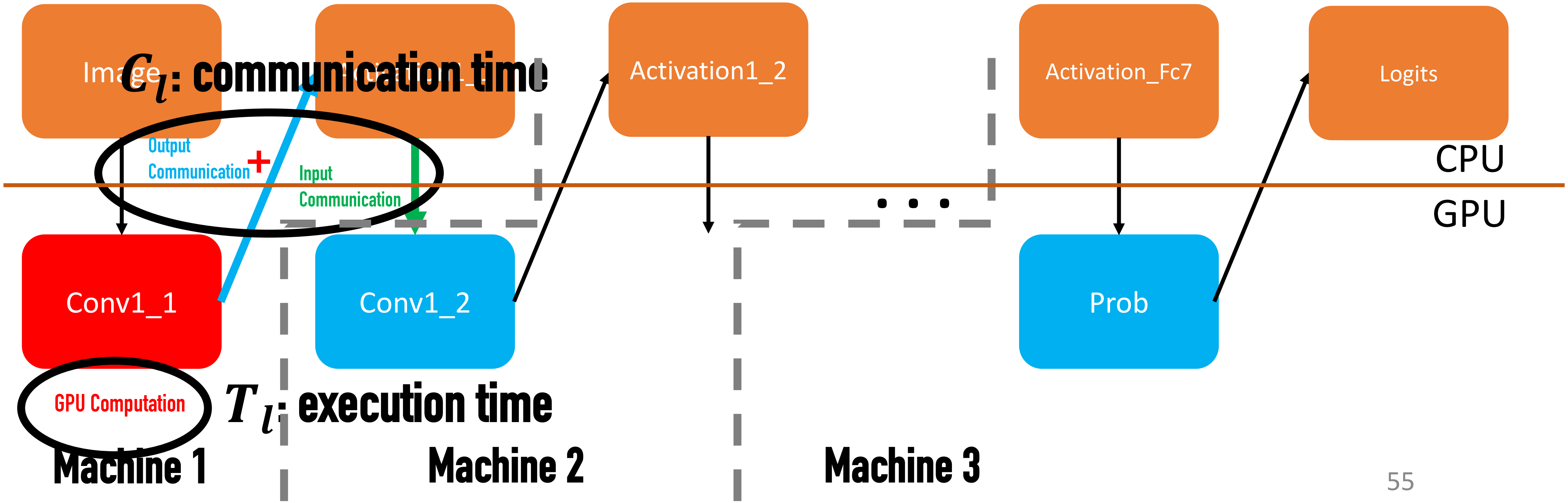


Dataflow Explain

- So, we can model the stage 1's execution time and communication time
- And we know if we split in here, we have cost of $\boldsymbol{C_l}$ to transmit data to other GPU



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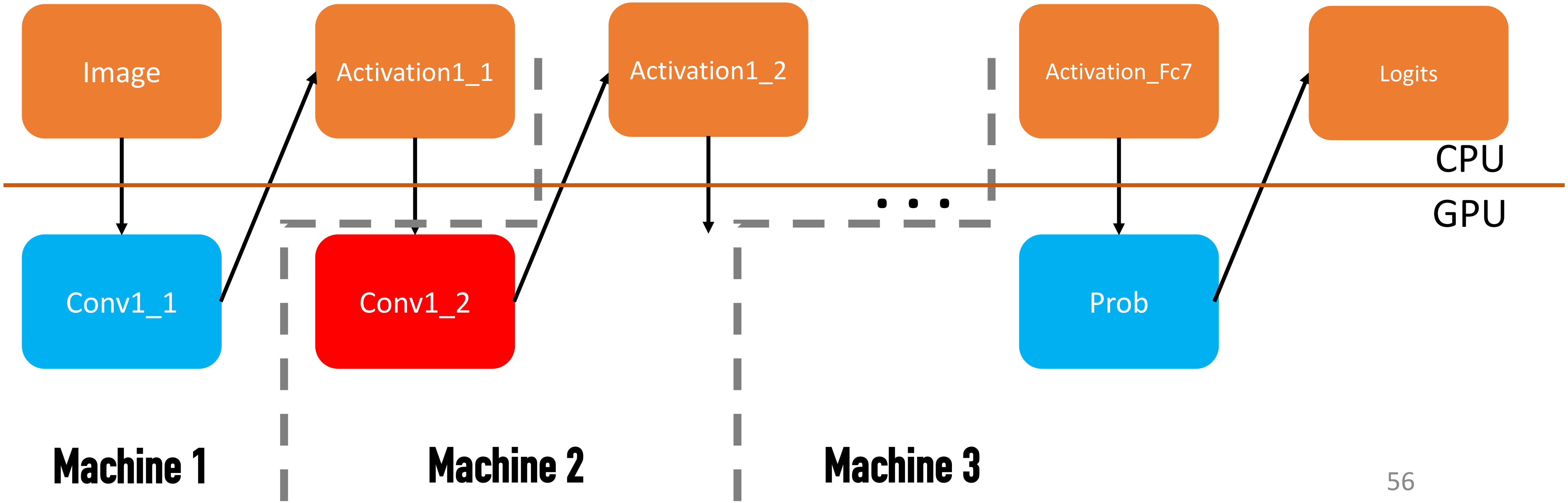

Move On to Partitioning

- We now have
  - T_l: the total computation time across the forward pass for layer l
  - C_l: the communication time to send output from layer l and input to layer l+1
  - a_l: the size of the activations of layer l
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  for micro-batch size N/T

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  for micro-batch size N/T

- With this information we can split model into stages to obtain the lowest computation time and load balancing among GPUs

Timeline Profiling

Dynamic-Programming Partitioning

Throughput Estimation

Profiling

- Profiles the DNN model with 1000 mini-batches, and records
  - T_l: the total computation time across the forward pass for layer l
  - a_l: the size of the activations of layer l
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$\left.\begin{array}{l} a_l \\ w_l \end{array}\right\}$ C_l: communication time

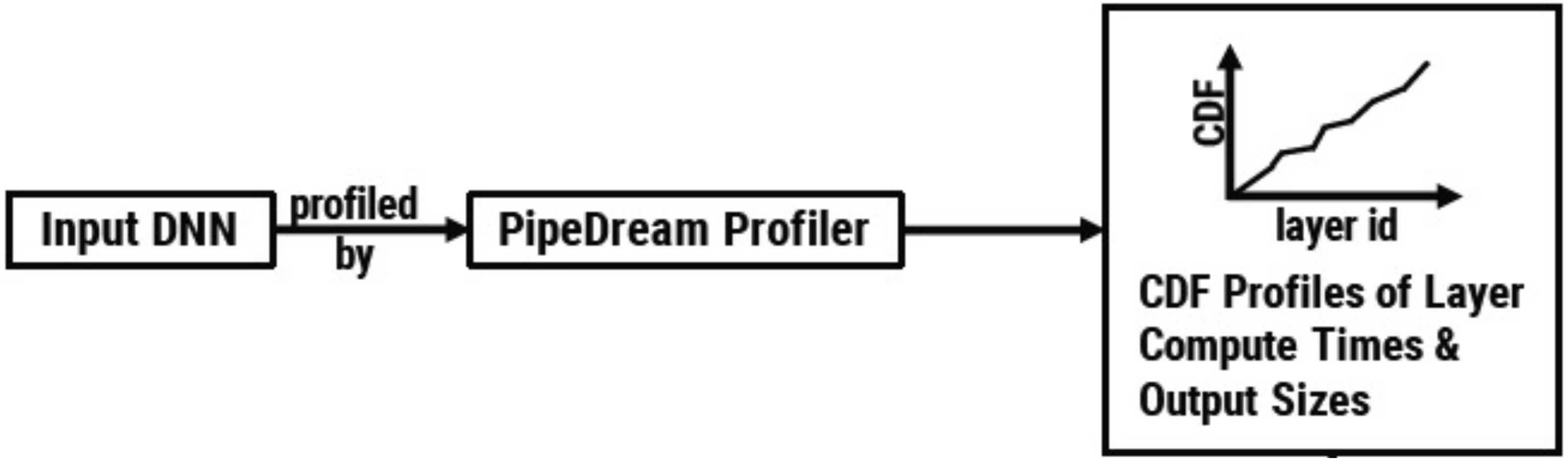

Fig. taken from [4].

Profiling

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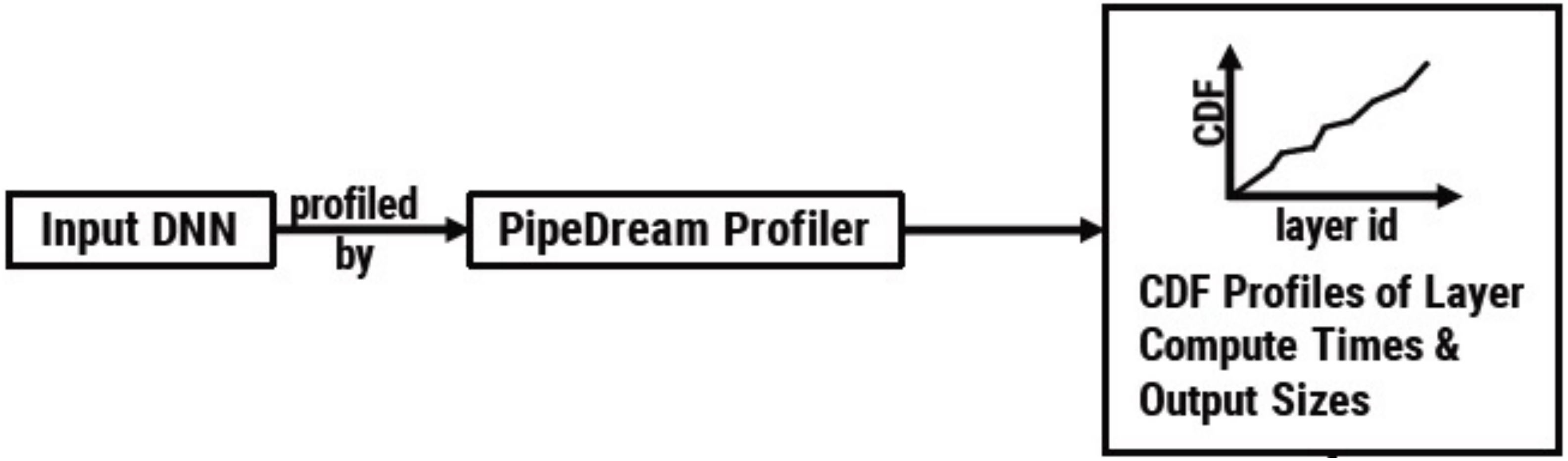

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Partitioning

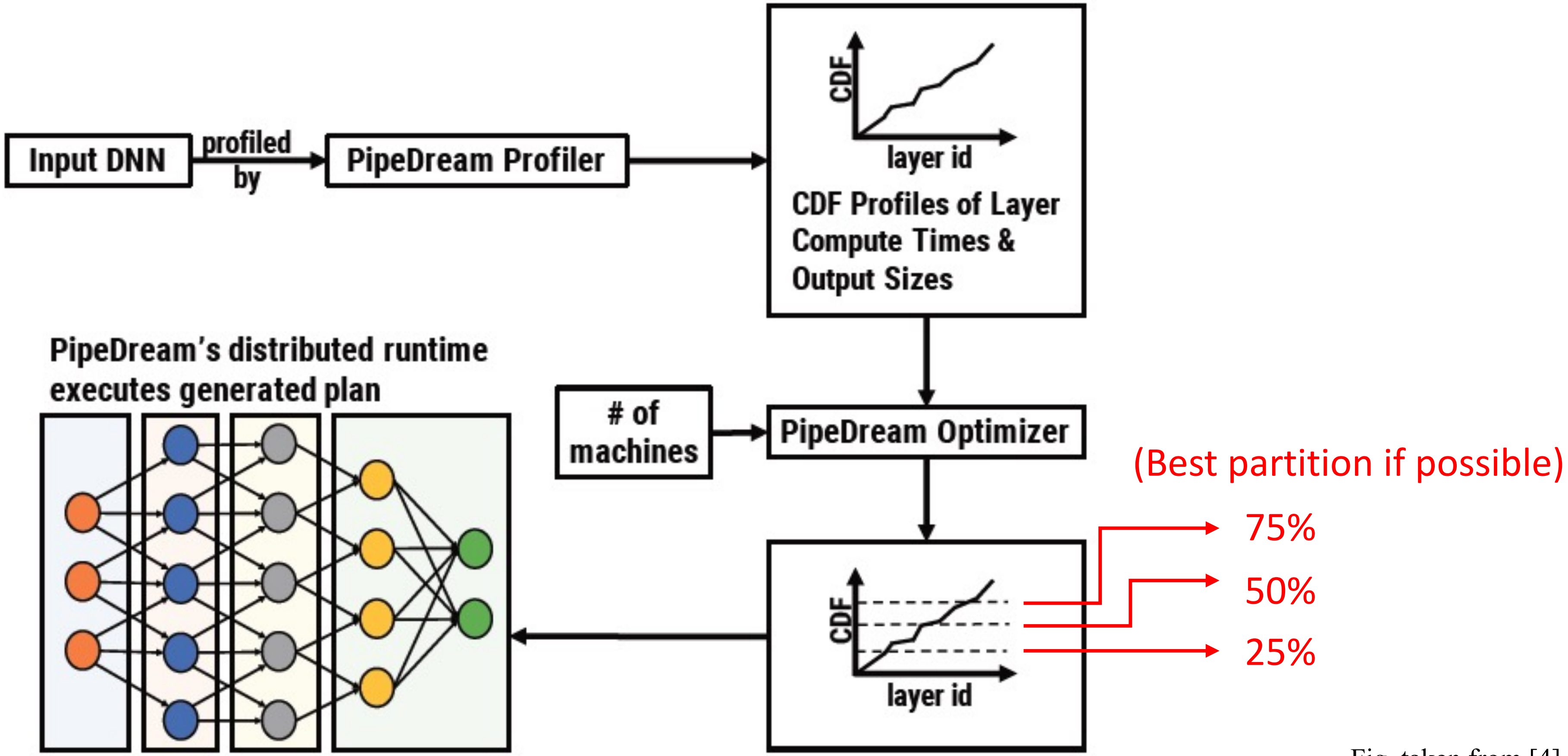
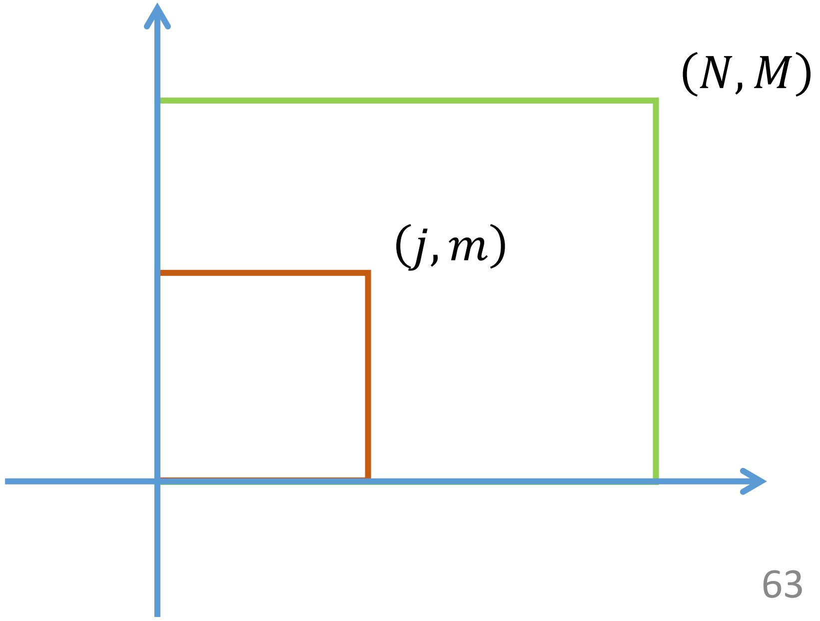


Fig. taken from [4].

Partitioning

- Find an optimal partition of N neural network layers among M machines with dynamic programming.
- Goal: minimize the time taken by the slowest stage.
- Sub-problem: partition layer 1 to j among m machines.
- Complexity
  - #subproblem: $O(NM)$
  - Complexity per subproblem: $O(NM)$
  - Overall complexity: $O(N^2M^2)$



Partitioning Algorithm with DP

$A(j,m)$: min(bottleneck stage_cost). j layers, m machines in total.
$T(i \longrightarrow j, m)$: compu_cost(stage(layer i to j)), replicated over m machines.

[Algorithm]

Case 1: Pure data parallelism (single stage)

$$A(j,m) = T(1 \to j, m)$$

Case 2: More than one stage

$$A(j,m) = \min_{1 \le i < j} \min_{1 \le m' < m} \max \begin{cases} A(i, m - m') \\ 2 \cdot C_i \\ T(i+1 \to j, m') \end{cases}$$

Output: $A(N, M)$

What we have:

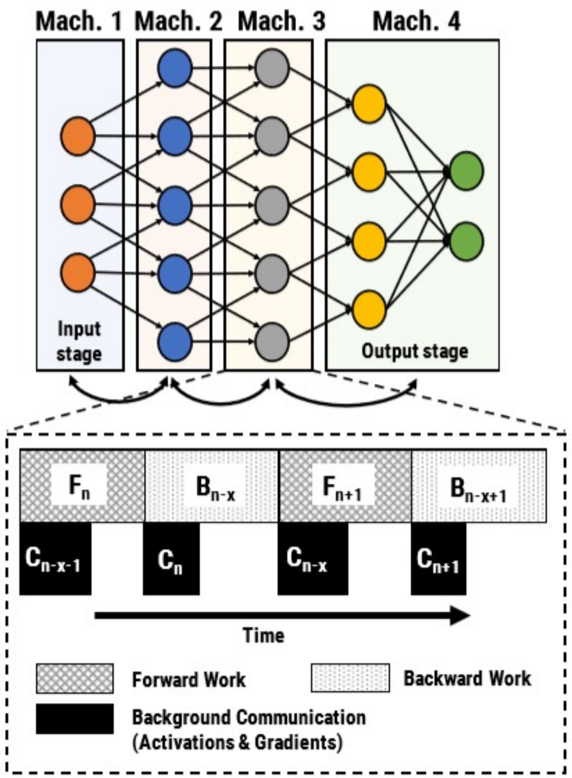
C_l: communication cost from layer i to i+1

W_l^m: weight update cost for layer i

$$T(i \to j, m) = \frac{1}{m} \max \left(\sum_{l=i}^{j} T_l, \sum_{l=i}^{j} W_l^m \right)$$

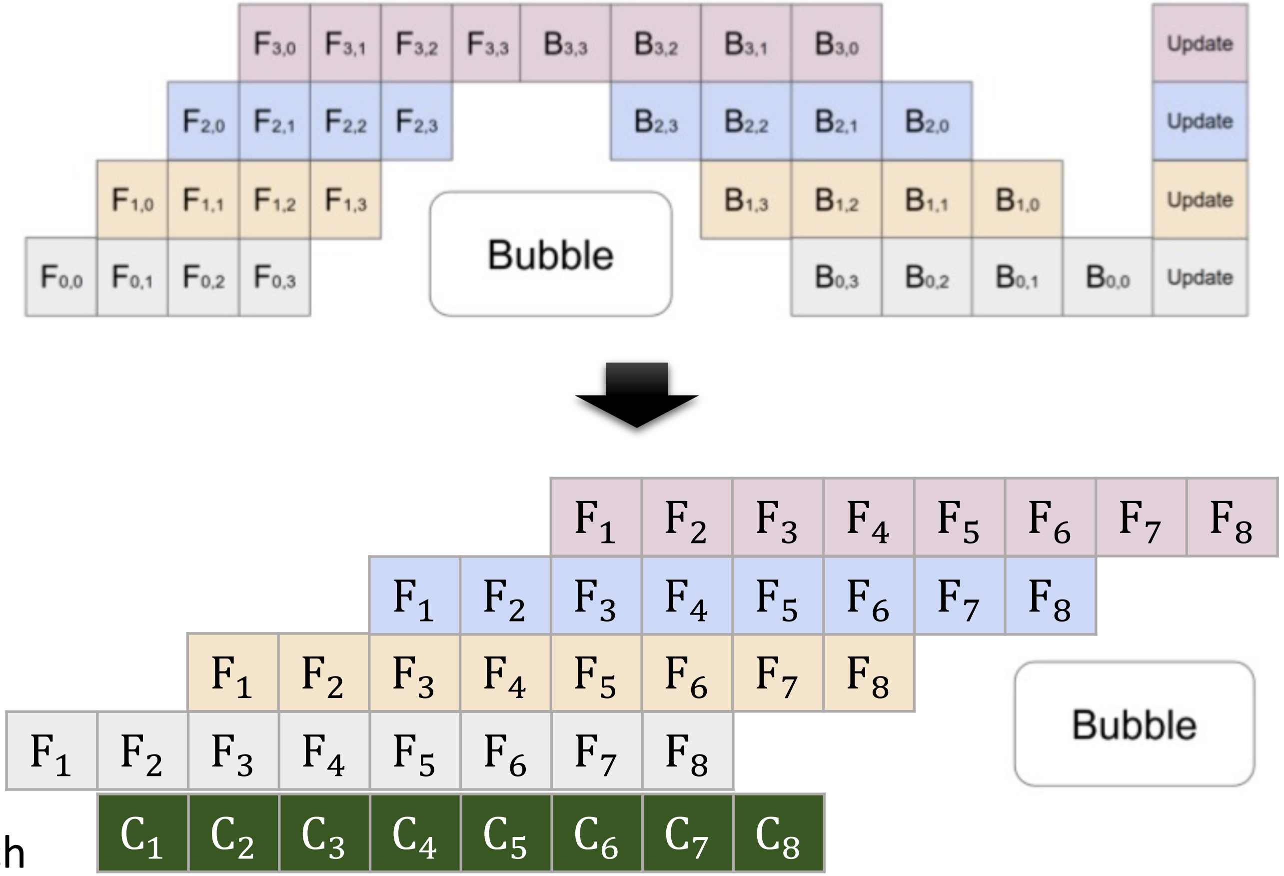
Pipelining in PipeDream vs. in GPipe

PipeDream



Hide communication latency by overlapping communication and computation of different mini-batch

GPipe



Same Order of Amortized Bubble Time

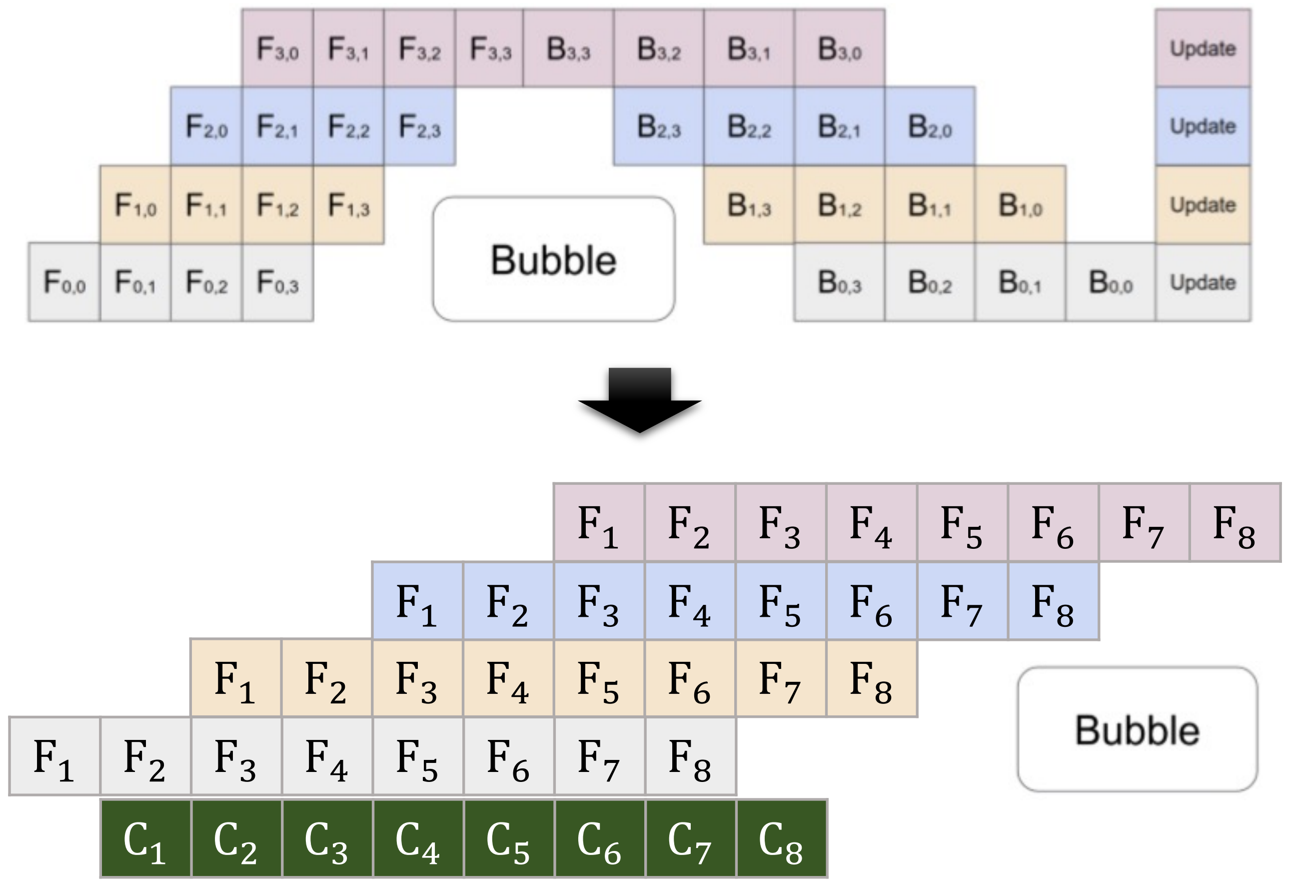
T = # of micro-batches
K = # of stages

$$Amortized\ bubble\ time = O\left(\frac{K-1}{T+K-1}\right)$$

$$Amortized\ bubble\ time = O\left(\frac{K-1}{T+2(K-1)}\right)$$

$$As\ T \gg K, O\left(\frac{K-1}{T+2(K-1)}\right) \cong O\left(\frac{K-1}{T+K-1}\right)$$

GPipe



Customized Partitioning Algorithm

$A(j,m)$: min(bottleneck stage_cost). j layers, m machines in total.
$T(i \longrightarrow j,m)$: compu_cost(stage(layer i to j)), replicated over m machines.

[Algorithm]

Case 1: Pure data parallelism (single stage)

$$A(j,m) = T(1 \rightarrow j, m)$$ **3. if …**

Case 2: More than one stage

2.

$$A(j,m) = \min_{1 \le i < j} \min_{1 \le m' < m} \max \begin{cases} A(i, m - m') \\ \boxed{2 \cdot C_i} \\ T(i+1 \rightarrow j, m') \end{cases}$$ **3. if …**

Output: $A(N,M)$

1.

What we have:

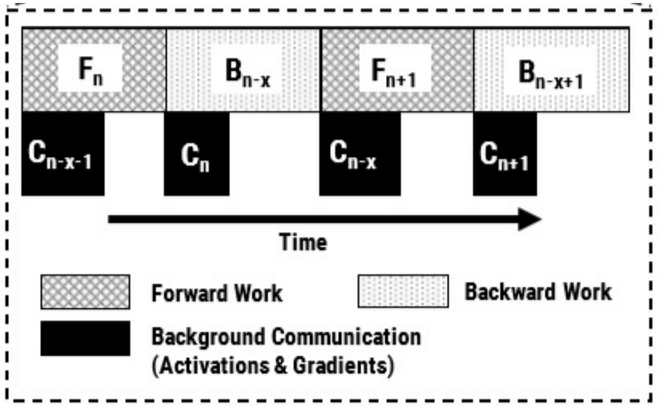
C_l: communication cost from layer i to i+1

~~W_l^m: weight update cost for layer i~~

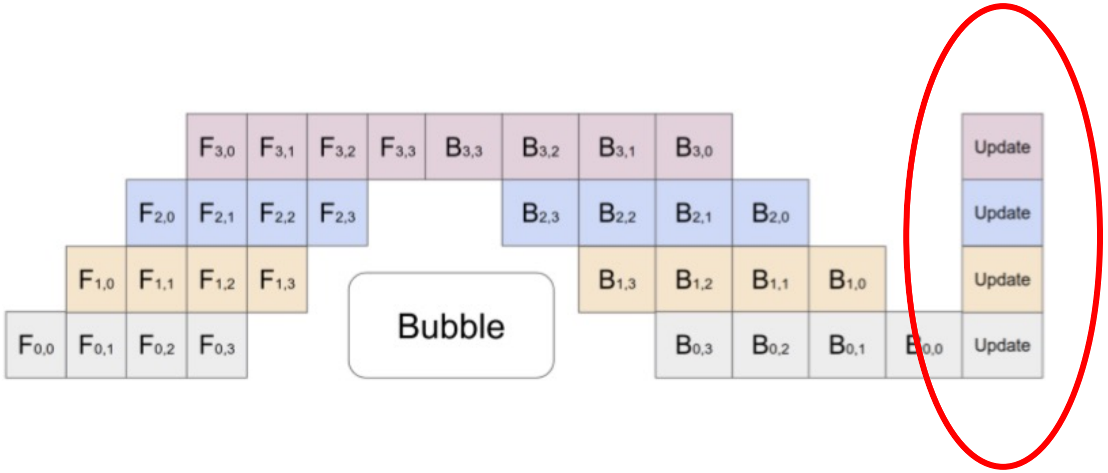
$$T(i \rightarrow j, m) = \frac{1}{m} \cancel{\max} \left(\sum_{l=i}^{j} T_l, \cancel{\sum_{l=i}^{j} W_l^m} \right)$$

1. No Within-Stage Weight Synchronization

PipeDream



GPipe



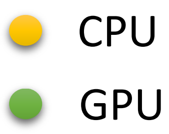
1F1B $\Longrightarrow$ within-stage weight synchronization / update (overlapped with computation)

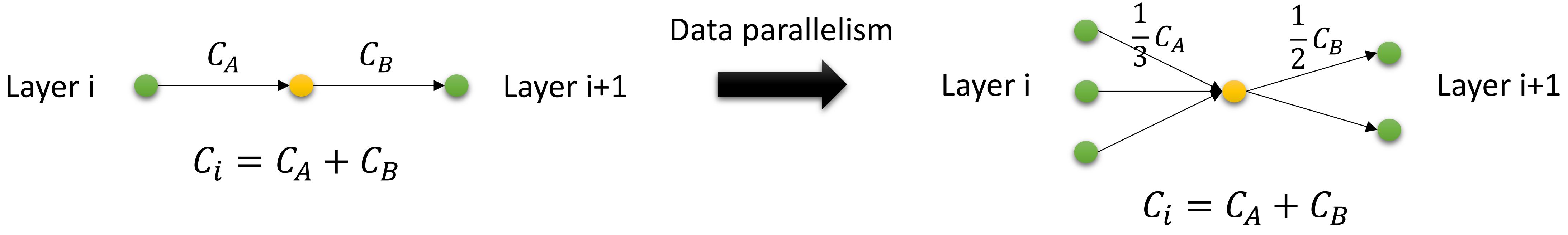
Weight synchronization / update is performed at the end of each mini-batch

$$T(i \rightarrow j, m) = \frac{1}{m} \max\left(\sum_{l=i}^{j} T_l, \sum_{l=i}^{j} W_l^m\right) \quad \Rightarrow \quad T(i \rightarrow j, m) = \frac{1}{m} \sum_{l=i}^{j} T_l$$

2. Communication Cost Estimator

- Inter-machine communication in PipeDream
  - ZeroMQ & Fast custom serialization
  - Cost estimator = $2C_i$, from i^{th} to $(i+1)^{th}$ layer
- Communication cost customized for our simulation
  - Communication flow goes through CPU node (limited bandwidth)
  - Remains $2C_i$





3. Upper Bound of Device Memory Usage

- The algorithm finds the optimal solution, i.e. the most balanced solution

$\Longrightarrow$ Tends to suggest pure data parallelism

  - Intuitively, model parallelism more or less induces imbalance
  - Mathematically, the minimal bottleneck cost is the average of the total cost

- To solve this problem, the memory limit is set
  - Filter out infeasible solution

$\boxed{L(i,j) = memory\ usage\ for\ layer\ i\ to\ j}$

$$A(j,m) = T(1 \rightarrow j, m) \qquad if\ L(1 \longrightarrow j) < Memory\ Limit$$

$$A(j,m) = \min_{1 \leq i < j} \min_{1 \leq m' < m} \max \begin{cases} A(i, m-m') \\ 2 \cdot C_i \\ T(i+1 \rightarrow j, m') \end{cases} \qquad if\ L(i+1 \longrightarrow j) < Memory\ Limit$$

Example of Partitioning Solutions

Memory Limit (MB)	Partition	Bottleneck cost
400	1->8 9->20 21->22 23->27	13166
448	1->7 8->15 16->22 23->27	11947
512	1->10 11->17 18->27	8419
1024	1->14 15->27	7182
2048	1->27	6776

Model: VGG. Profiled with a fixed batch size.

\# of layers = 27

\# of machines = 4

```
dp> setprof -f ../case/vgg_w4mb8.txt
dp> memlim 400
dp> partition

Profile: ../case/vgg_w4mb8.txt
========== Partition ==========
# of layers : 27
# of workers: 4
stage      layer      reps   cost
   1    1->   8         1   13166
   2    9->  20         1   12522
   3   21->  22         1     996
   4   23->  27         1     625
Pipeline bottleneck cost: 13166

dp> memlim 448
dp> partition

Profile: ../case/vgg_w4mb8.txt
========== Partition ==========
# of layers : 27
# of workers: 4
stage      layer      reps   cost
   1    1->   7         1   11337
   2    8->  15         1   11947
   3   16->  22         1    3930
   4   23->  27         1     625
Pipeline bottleneck cost: 11947
```

```
dp> setprof -f ../case/vgg_w4mb8.txt
dp> memlim 512
dp> partition

Profile: ../case/vgg_w4mb8.txt
========== Partition ==========
# of layers : 27
# of workers: 4
stage      layer      reps   cost
   1    1->  10         2   8418.5
   2   11->  17         1     7848
   3   18->  27         1     3159
Pipeline bottleneck cost: 8418.5

dp> memlim 1024
dp> partition

Profile: ../case/vgg_w4mb8.txt
========== Partition ==========
# of layers : 27
# of workers: 4
stage      layer      reps   cost
   1    1->  14         3  7181.67
   2   15->  27         1     5558
Pipeline bottleneck cost: 7181.67

dp>
```

```
dp> setprof -f ../case/vgg_w4mb8.txt
dp> memlim 2048
dp> partition

Profile: ../case/vgg_w4mb8.txt
========== Partition ==========
# of layers : 27
# of workers: 4
stage      layer      reps   cost
   1    1->  27         4  6775.75
Pipeline bottleneck cost: 6775.75

dp>
```

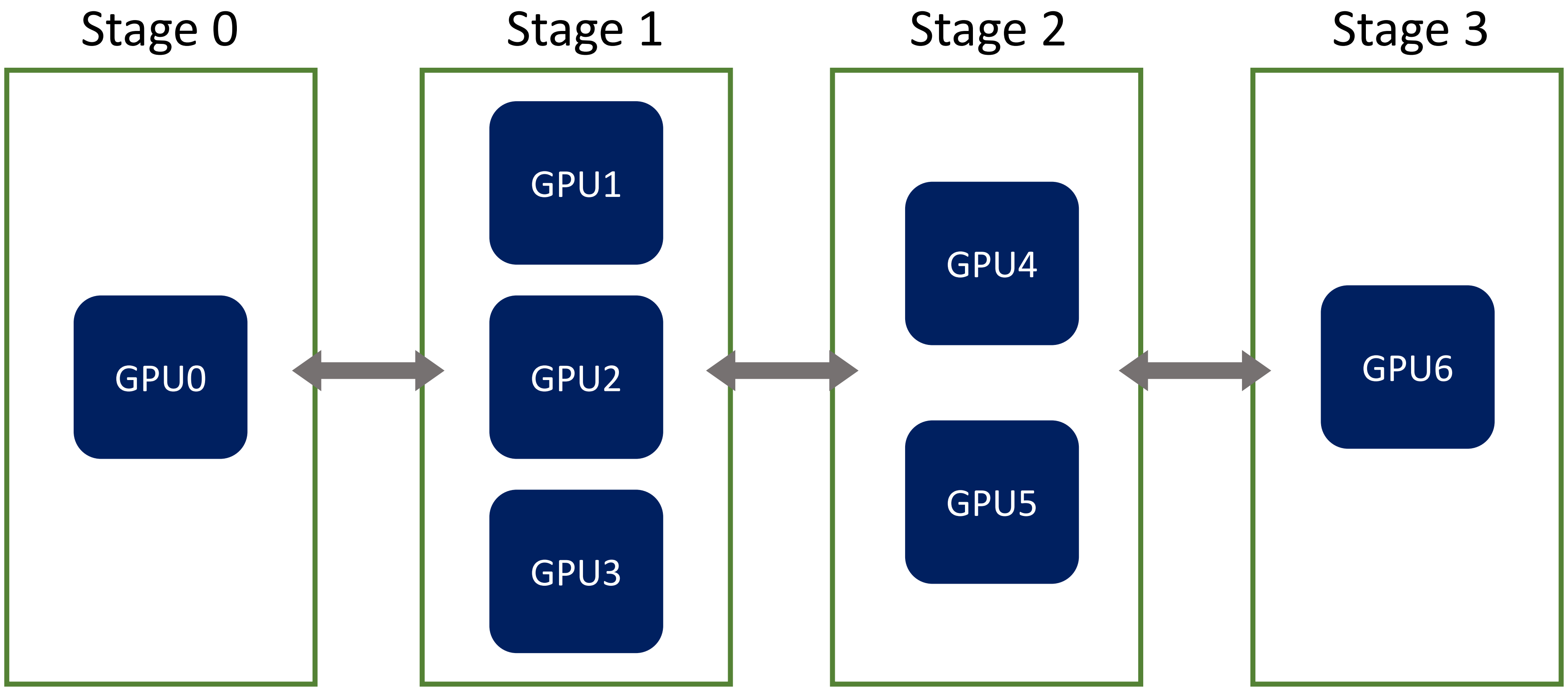
Timeline Profiling

Dynamic-Programming Partitioning

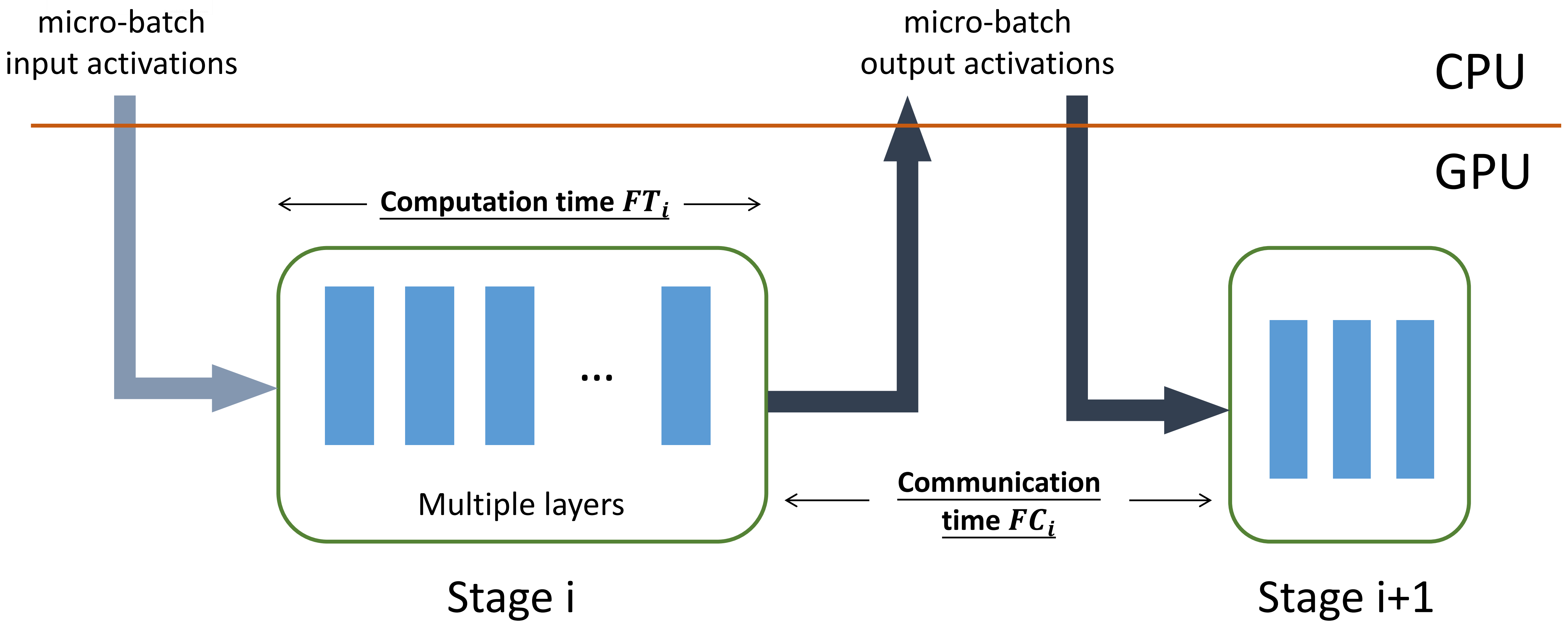
Throughput Estimation

Model Partitioning

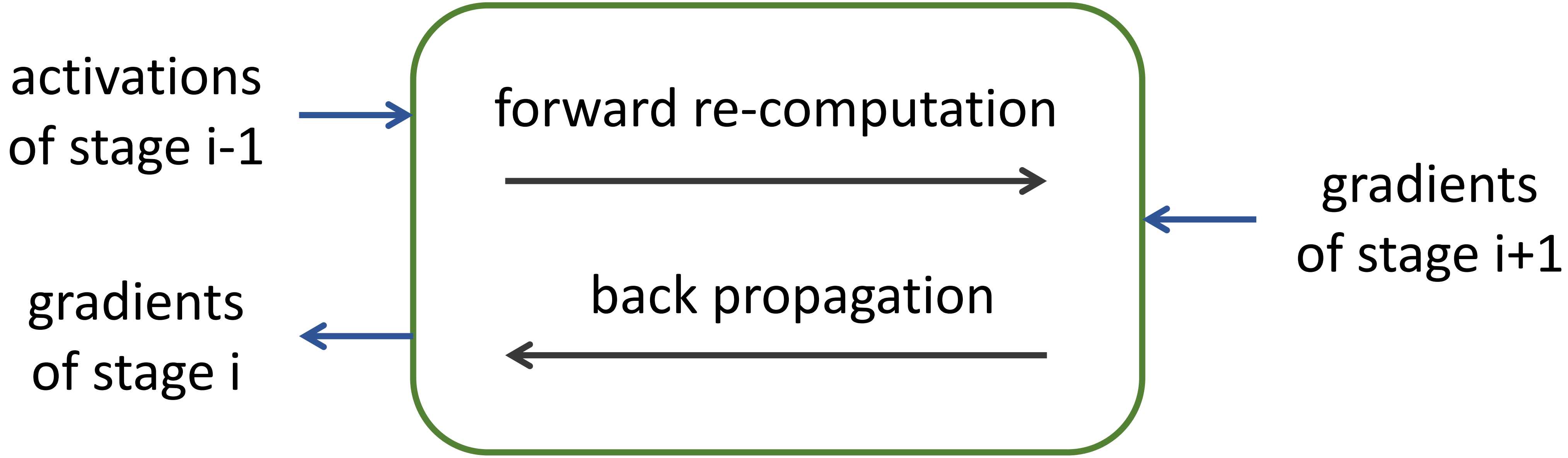
- With the obtained partition from previous steps…



Forward Pass

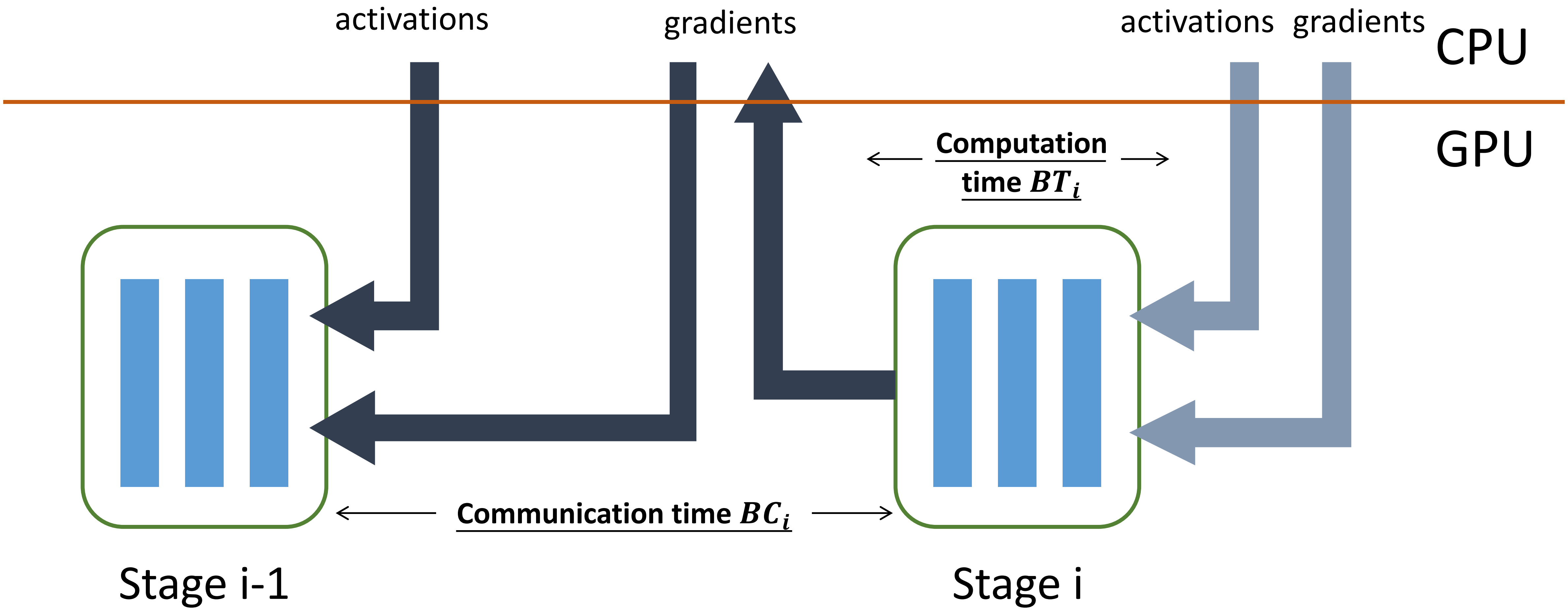


Backward Pass



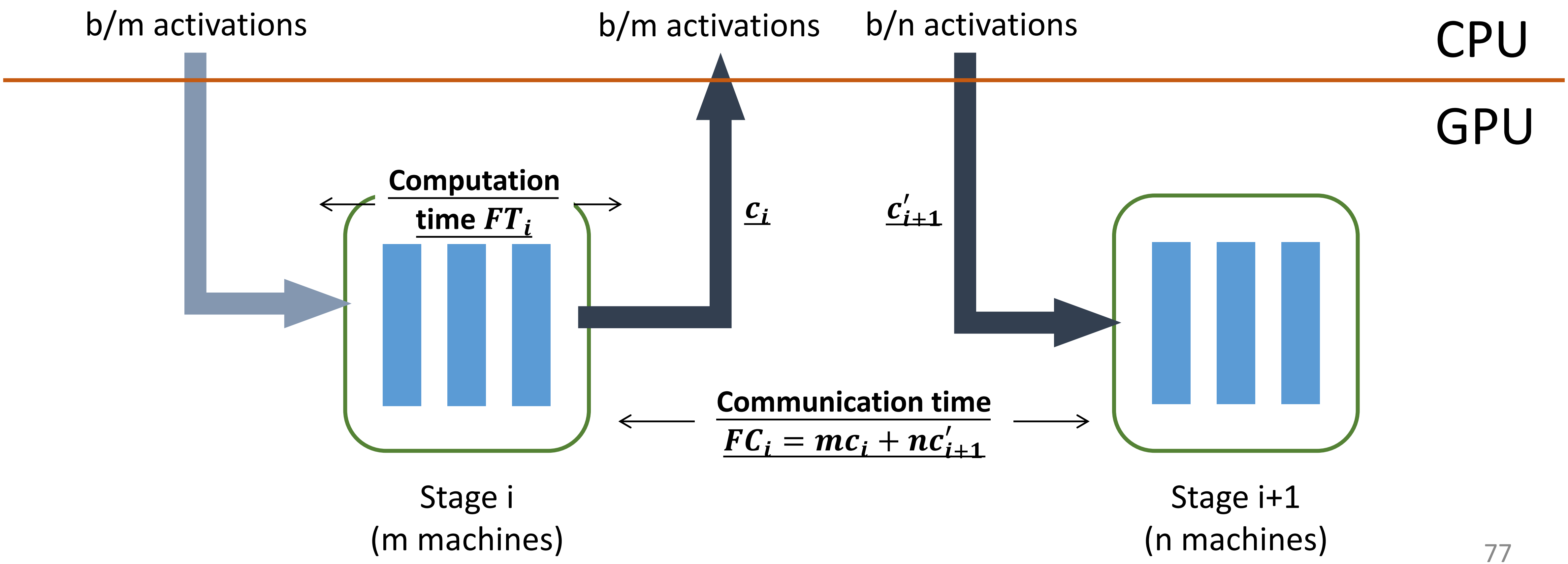
Stage i

Backward Pass



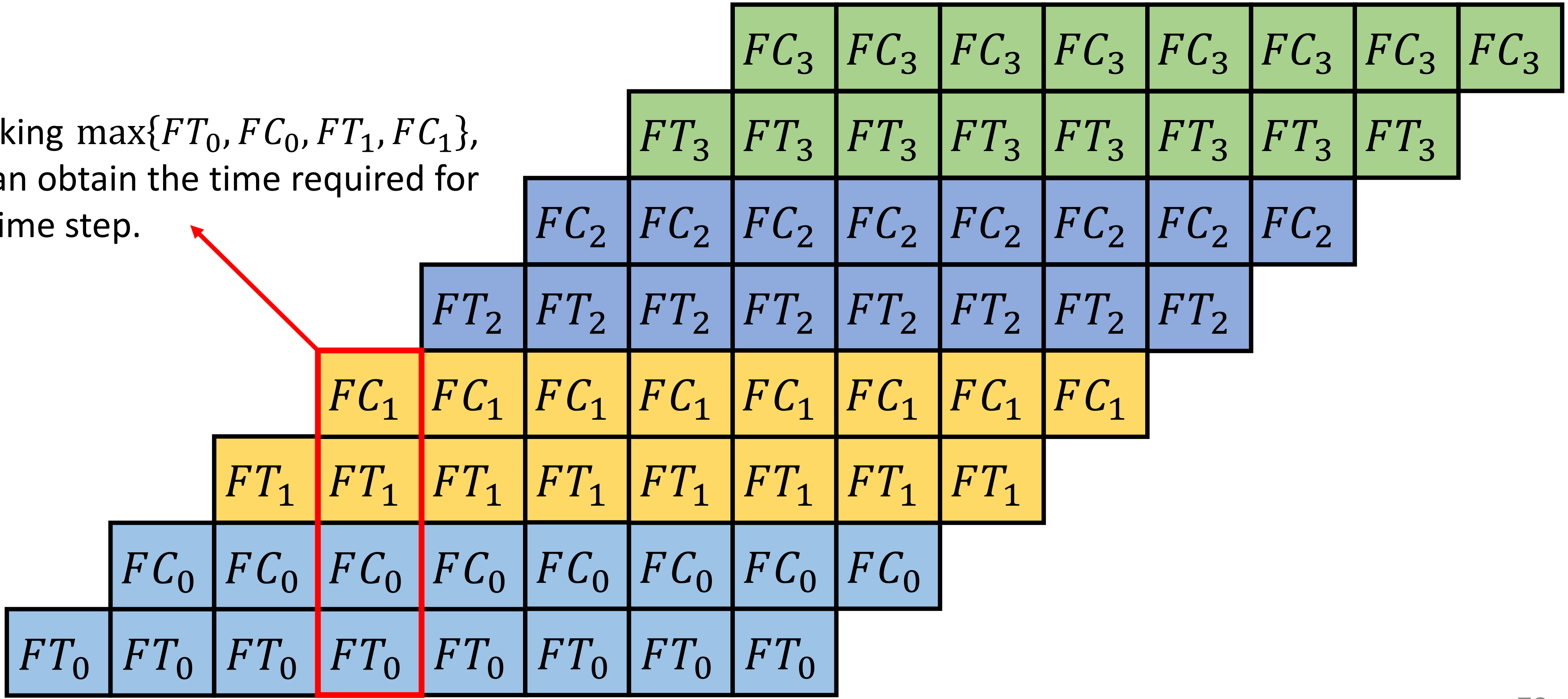
GDP Time Estimation

- Let micro-batch size be b

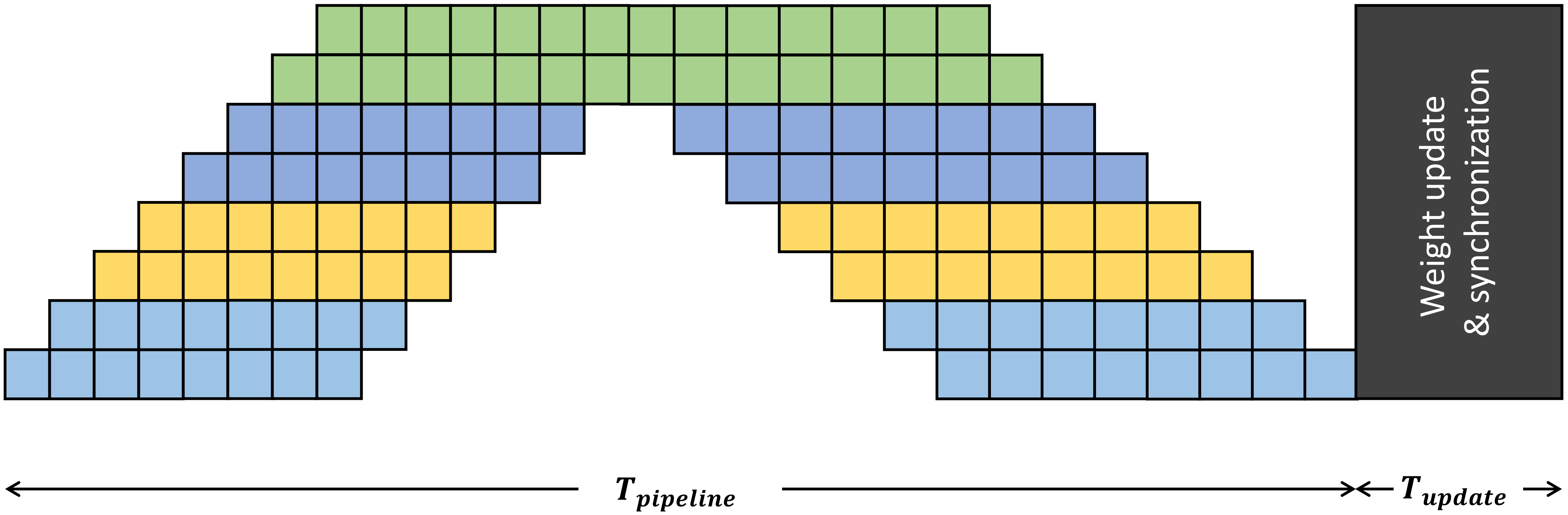


Pipelining

By taking $\max\{FT_0, FC_0, FT_1, FC_1\}$, we can obtain the time required for this time step.



Throughput Estimation



$$T_{cycle} = T_{pipeline} + T_{update}$$

$$throughput = \frac{mini\text{−}batch\ size}{T_{cycle}}$$

Experiments

Environments

- Intel® Core™ i7-8700 with 32G RAM
- GeForce RTX 2080 Ti (CUDA 10.1)
- Ubuntu 16.04.6 LTS
- Python2.7 with TensorFlow 1.14

Parameters

- NN models: VGG19(1.17G) and ResNet-152(3.63G) and SE-ResNeXt(0.49G) all with input image size (448, 448, 3)
- #GPU: 1, 2, 4, 8
- Mini-batch size: 16, 32, 64, 128
- #Micro-batch: 2, 4, 8, 16
- Methods: single GPU, Vanilla DP, GPipe with heuristic, Black GPipe

⟶ **Record throughput: #images processed per second**

Experimental Results

Observation

- on mini-batch size and #micro-batch

mini-batch size \ #micro-batch	2	4	8	16
16	7.91	10.42	9.48	5.25
32	10.27	10.25	11.62	10.39
64	-	13.51	12.06	12.34
128	-	-	**16.14**	13.18

same micro-batch size,
larger #micro-batch
→ higher throughput

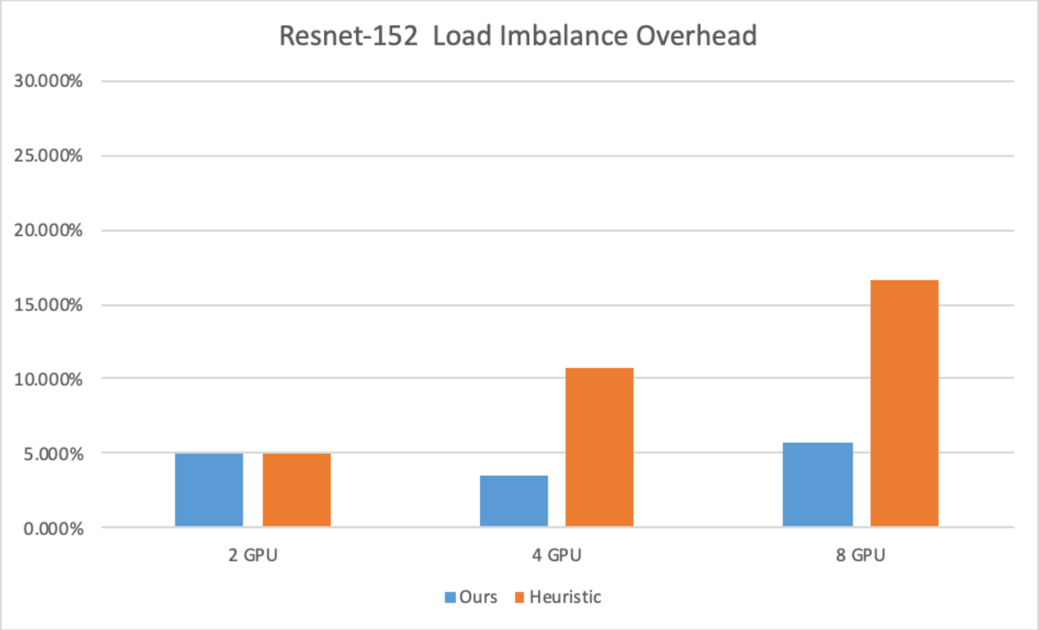
OOM due to large batch size

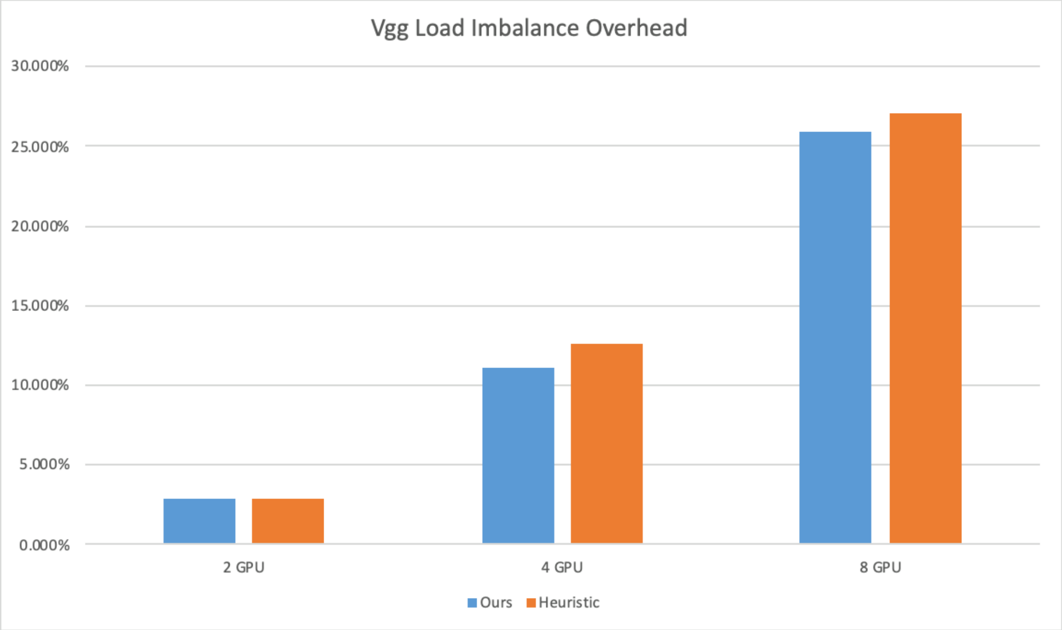
Larger batch size & more batches
→ higher throughput

same #micro-batch,
larger mini-batch size
→ higher throughput

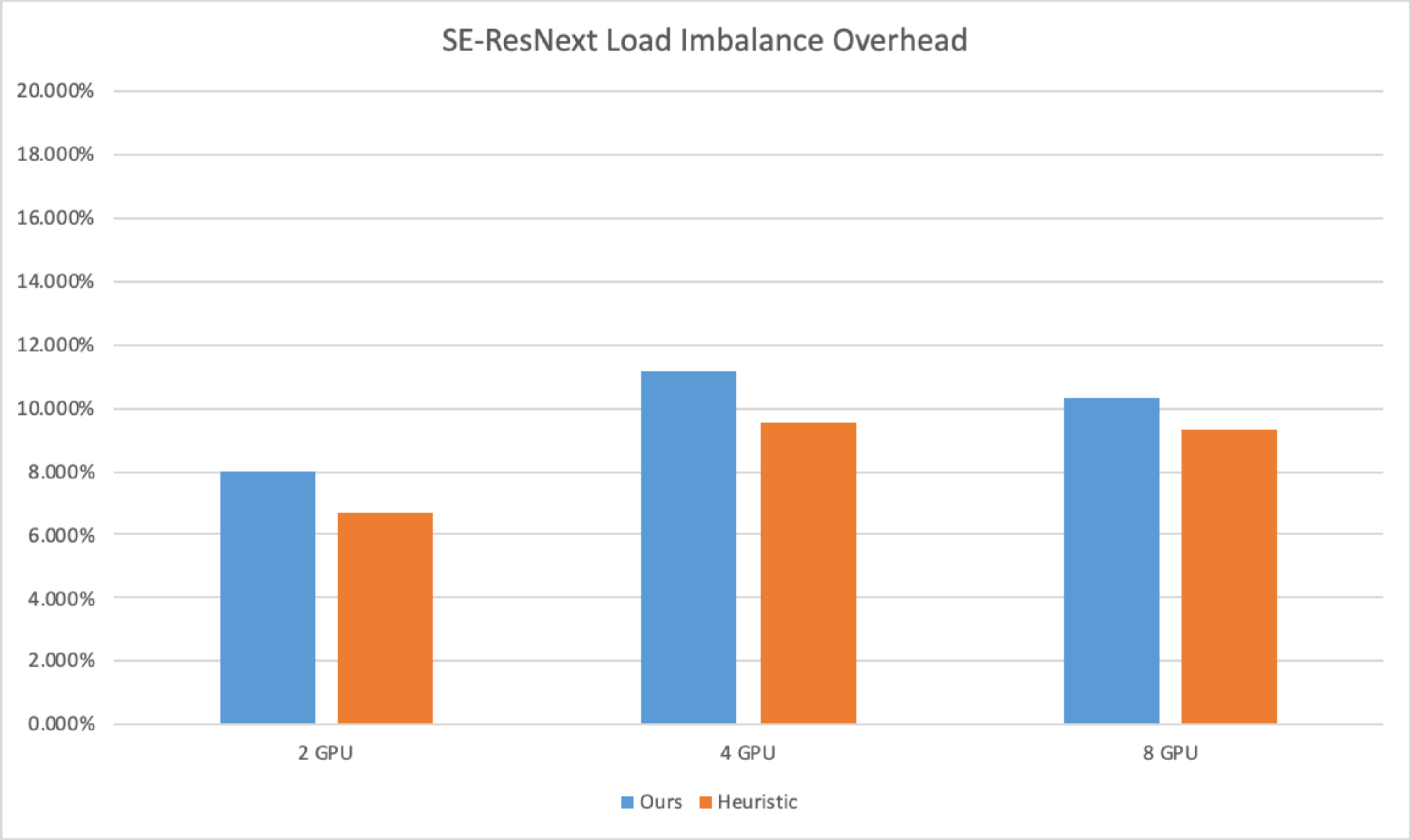
(VGG19, 2 GPUs, Ours Partitioning)

Load Balancing

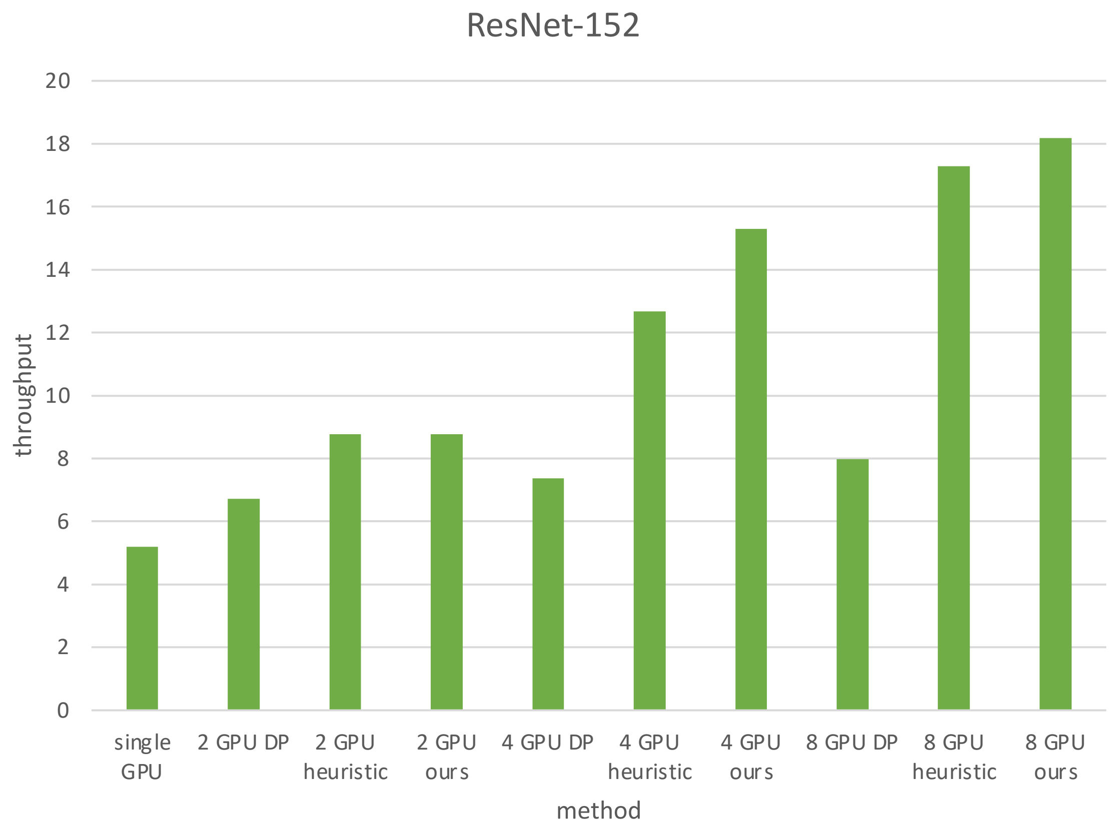




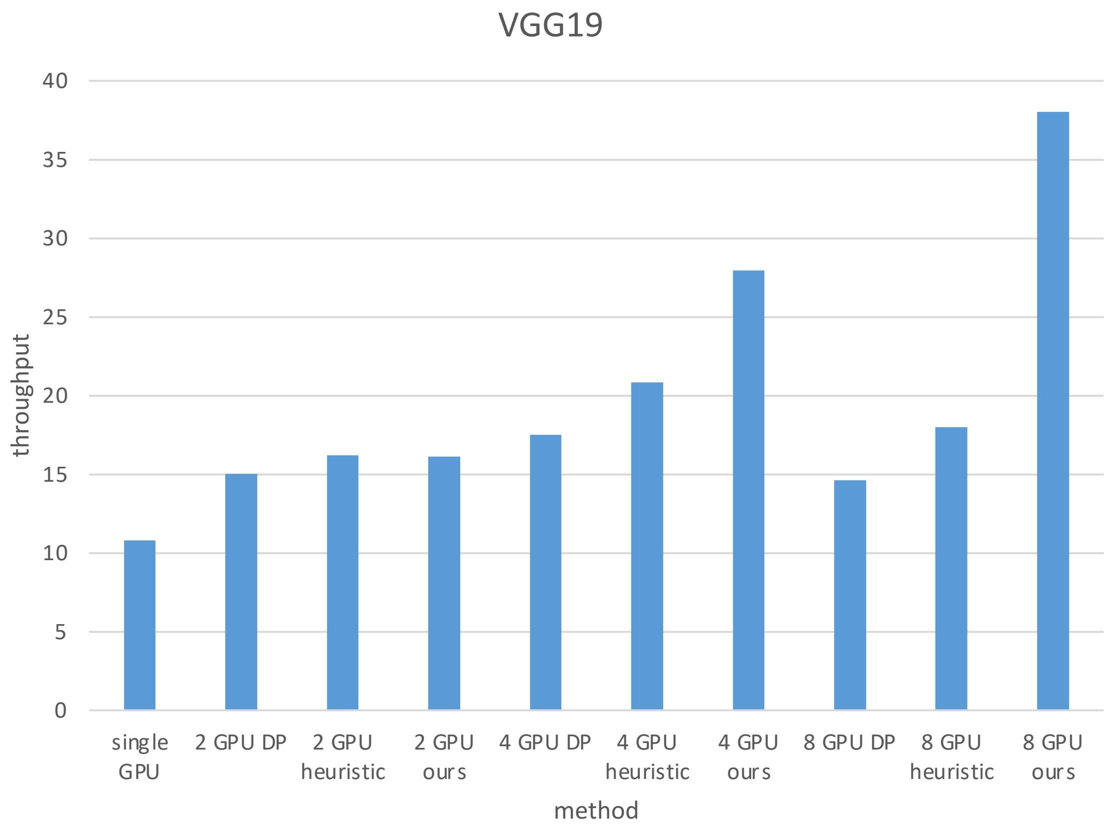
Load Balancing



Throughput

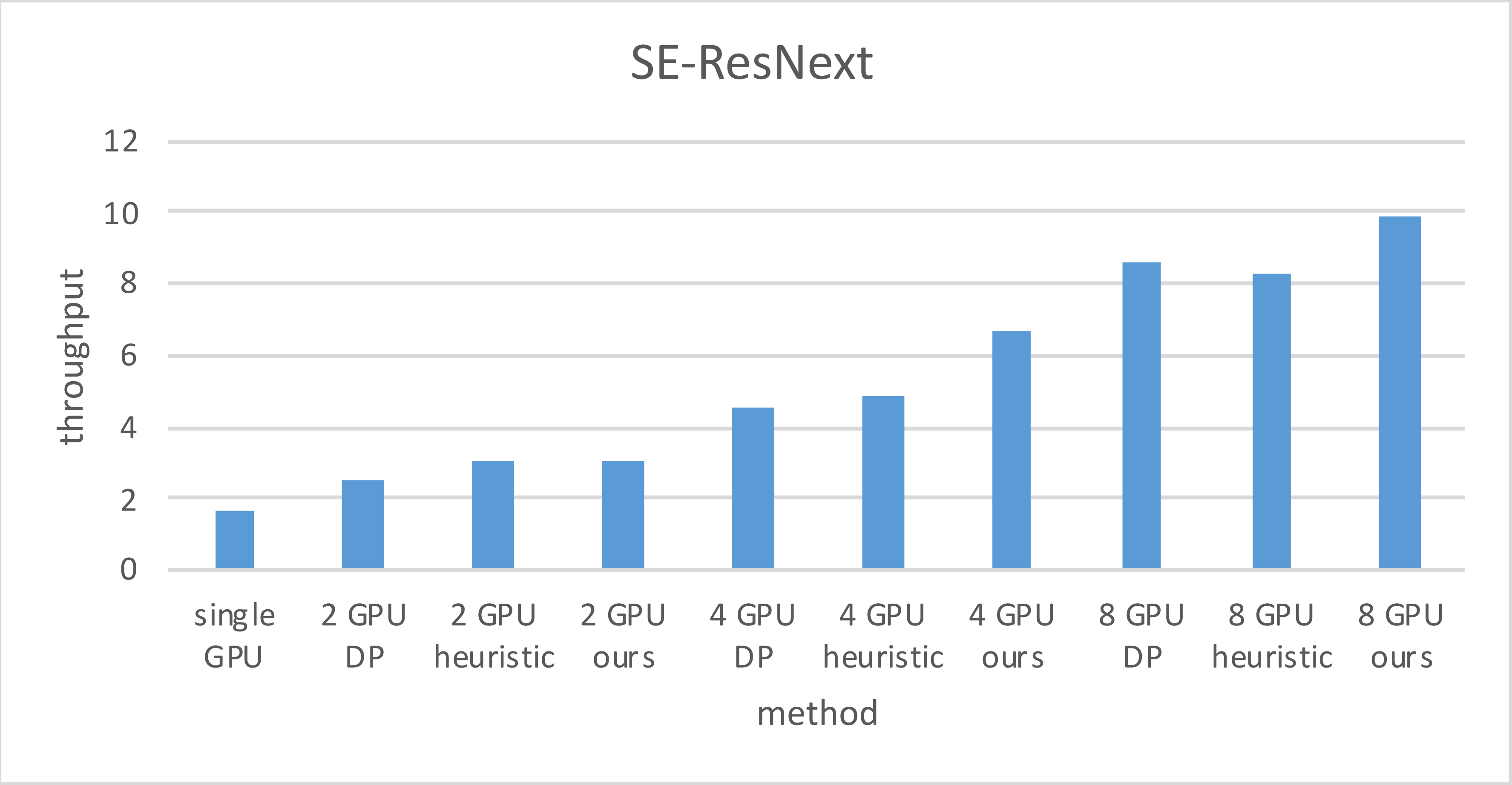


ResNet-152
throughput
method
0
2
4
6
8
10
12
14
16
18
20
single GPU
2 GPU DP
2 GPU heuristic
2 GPU ours
4 GPU DP
4 GPU heuristic
4 GPU ours
8 GPU DP
8 GPU heuristic
8 GPU ours



VGG19
throughput
method
0
5
10
15
20
25
30
35
40
single GPU
2 GPU DP
2 GPU heuristic
2 GPU ours
4 GPU DP
4 GPU heuristic
4 GPU ours
8 GPU DP
8 GPU heuristic
8 GPU ours

Throughput



SE-ResNext
throughput
12
10
8
6
4
2
0
single GPU
2 GPU DP
2 GPU heuristic
2 GPU ours
4 GPU DP
4 GPU heuristic
4 GPU ours
8 GPU DP
8 GPU heuristic
8 GPU ours
method

Conclusion

Conclusion

- We profiled the computation/communication time of each layer in a neural network, and applied PipeDream-like partitioning algorithm to split the model into different stages.
- We proposed an approach to simulate multi-GPUs system to estimate the Black GPipe training time and throughput.
- The experiments showed that our partitioning algorithm is better than the heuristic-based one when comparing the estimated throughput.
- The experiments showed that our partitioning algorithm is better than the heuristic-based one on larger models when comparing load imbalance overhead
- Black GPipe can achieve higher throughput with larger micro-batch size and larger #micro-batch.

Future Work

Some potential improvement…

- Checkpoints for re-computation
- Partitioning algorithm
  - Take #micro-batch into consideration
  - Better integration of DP overhead and BP time
  - More accurate memory constraint
- Run the experiments on multi-GPUs server

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THANKS