HetPipe: Enabling Large DNN Training on (Whimpy) Heterogeneous GPU Clusters through Integration of Pipelined Model Parallelism and Data Parallelism

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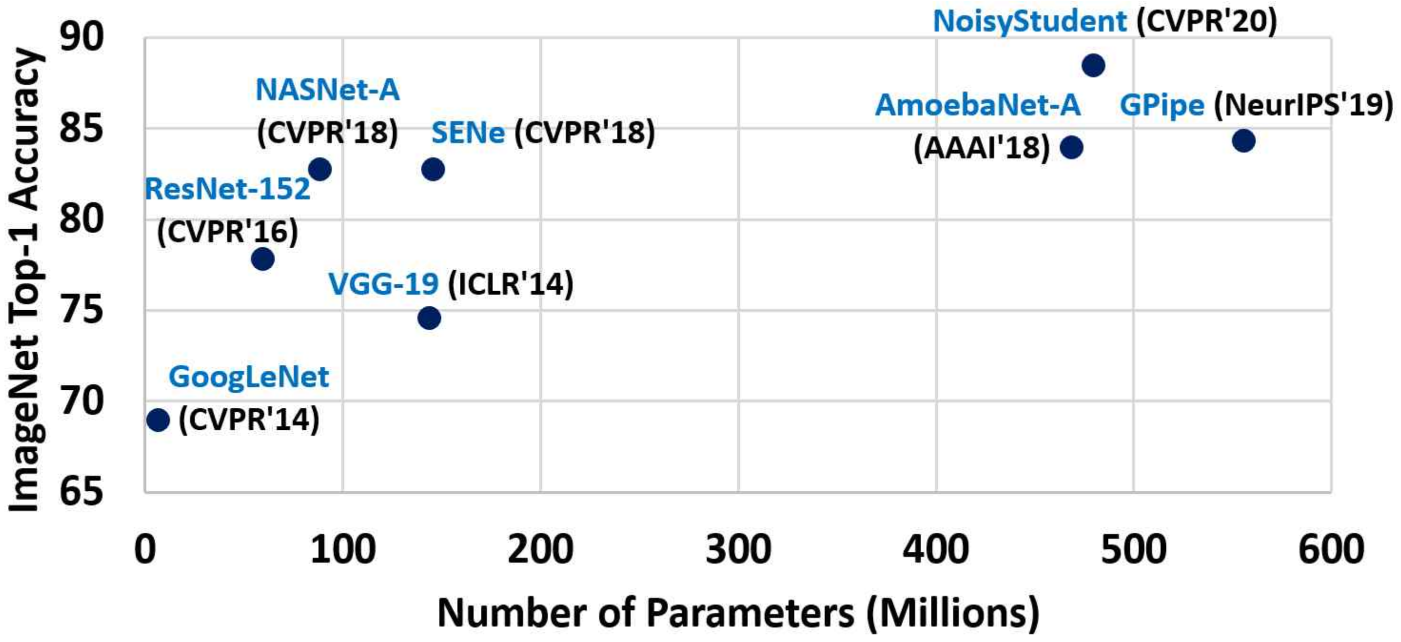
Contents

Motivation

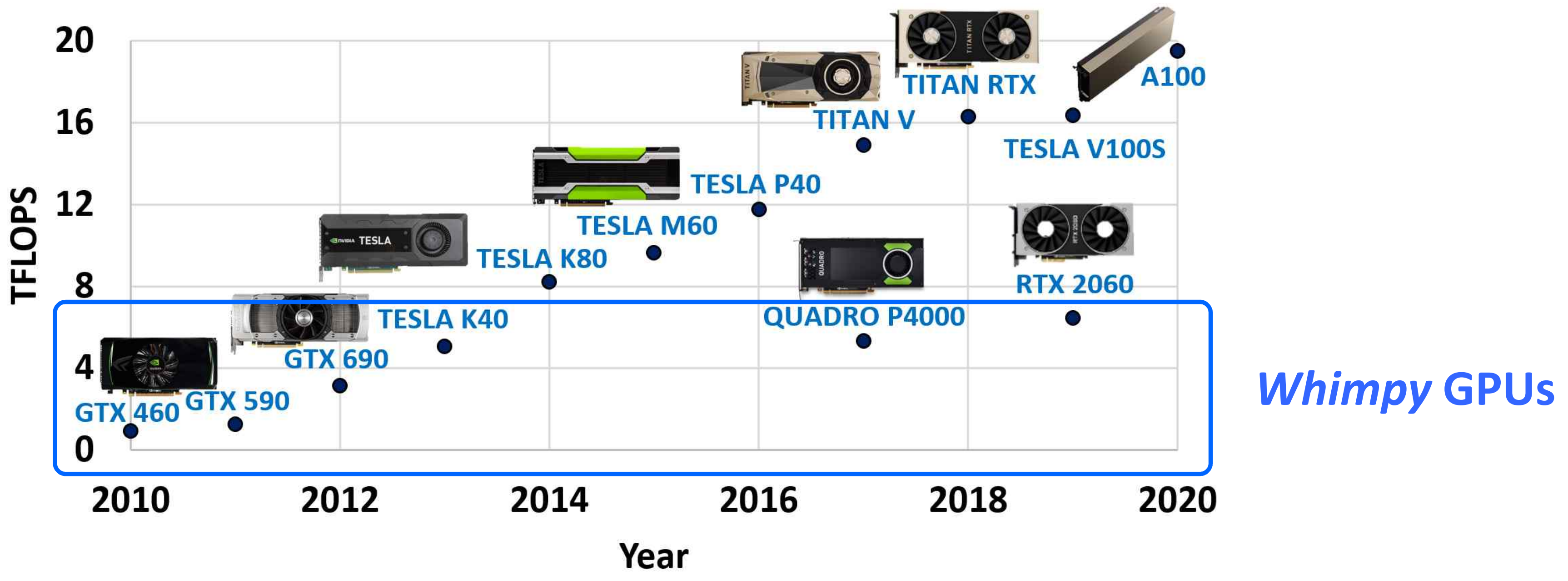
- DNN (Deep Neural Network) models continue to grow



- Need more powerful GPUs for training!

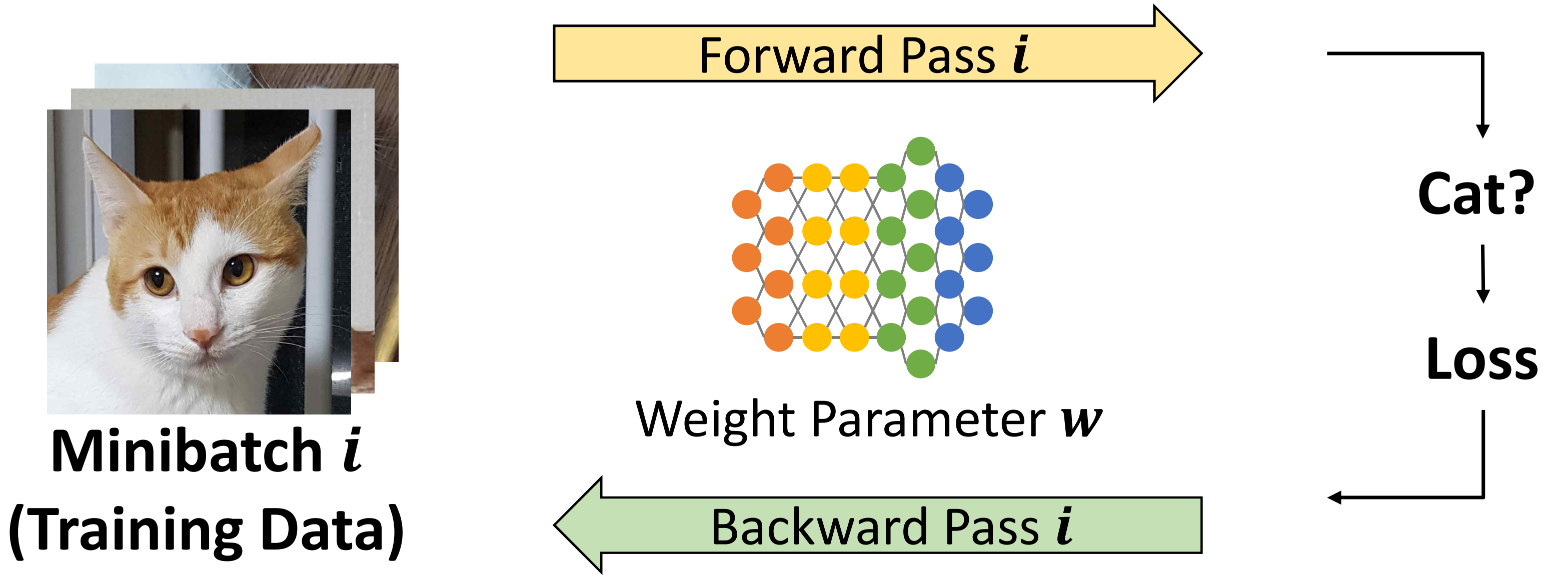
Motivation

- Short release cycle of new GPU architectures



- Use of heterogeneous GPUs is inevitable!
- What to do with *whimpy* GPUs?

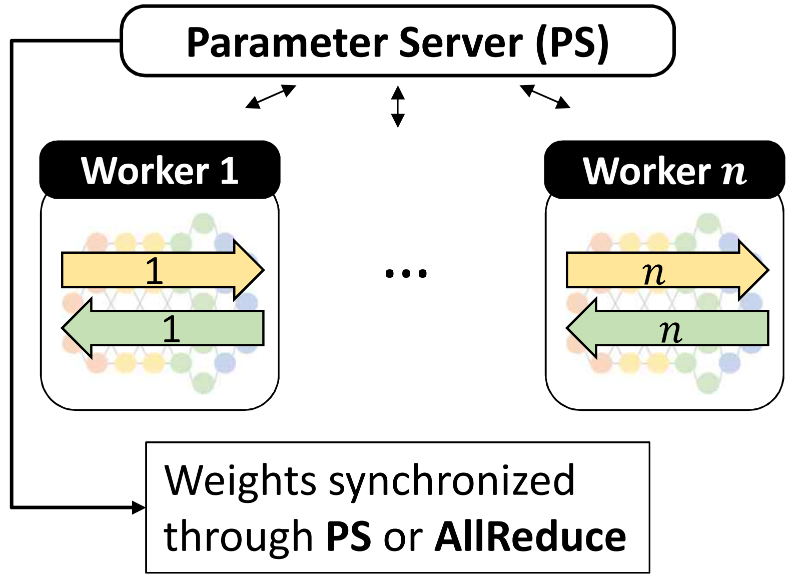
DNN Training



$$w_{i+1} = w_i - \eta \cdot u_i$$

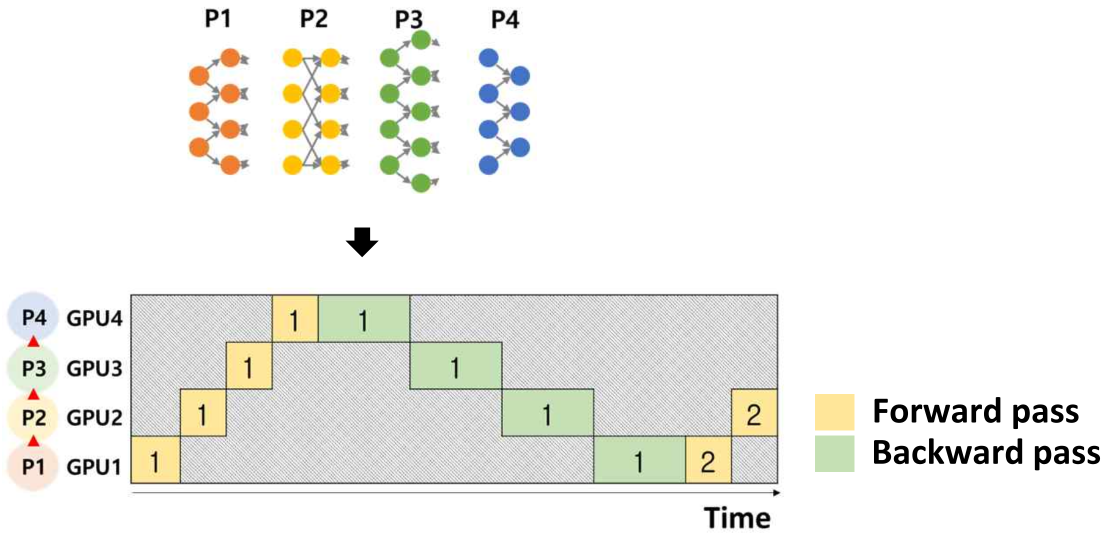
Parallelizing DNN Training

- Data parallelism (DP)



- GPU memory limitation

- Model parallelism (MP)

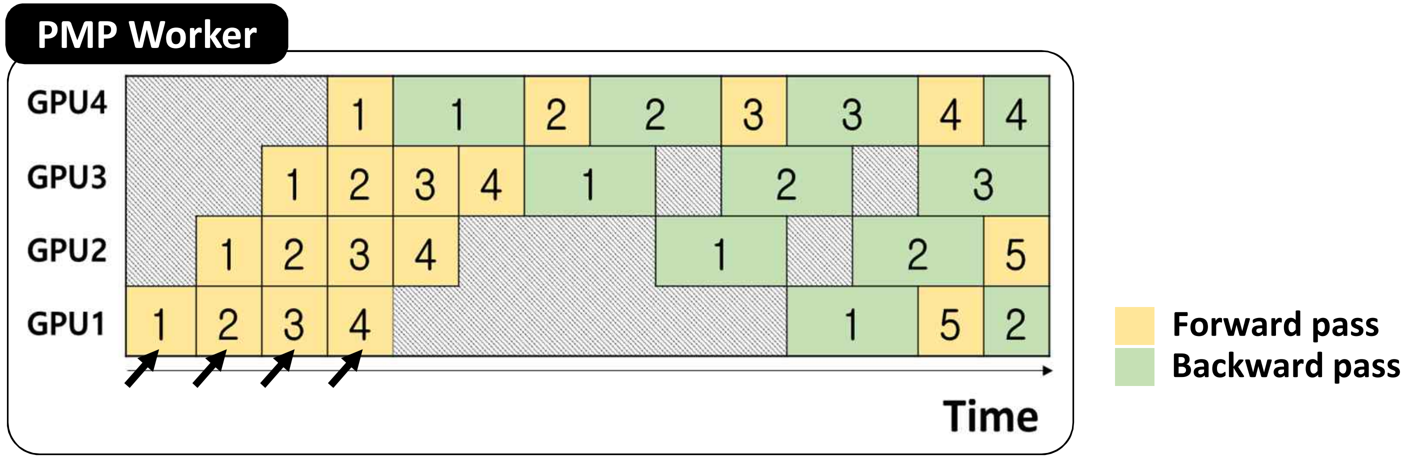


- Low GPU utilization

Parallelizing DNN Training

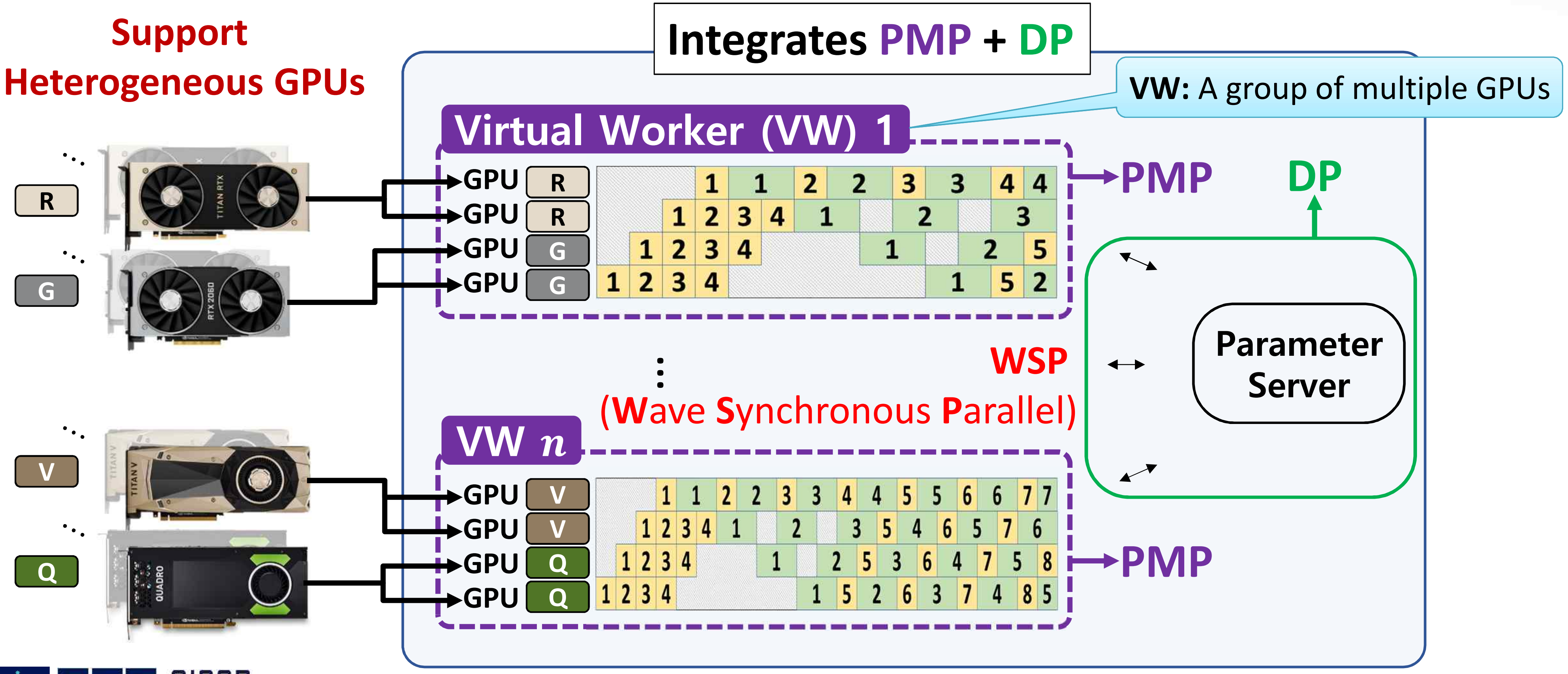
- **Attempts to improve MP utilization**
  - Pipelined model parallelism (PMP)

- **PipeDream** [SOSP'19]
- **GPipe** [NIPS'19]

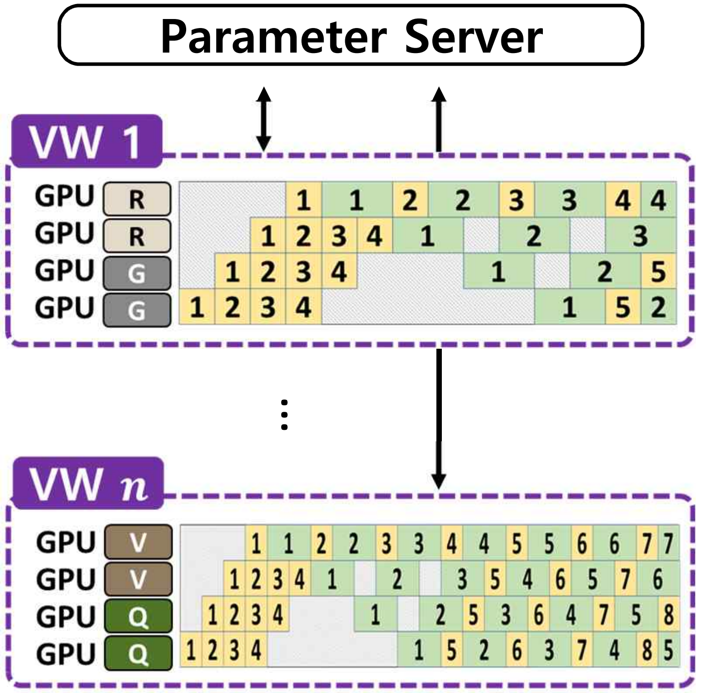


- Designed for homogeneous GPUs
- Designed for a single PMP worker

HetPipe in a Nutshell



Challenges in integration PMP+DP in Heterogeneous GPUs



- What weight version should be used by each VW to synchronize with other VWs?

- How do we reduce virtual worker stragglers when we consider DP?

⋮

Many more in the paper

HetPipe Contributions

Enable Large DNN Training on Heterogeneous GPUs

Aggregate heterogeneous resources

Reduce the straggler problem

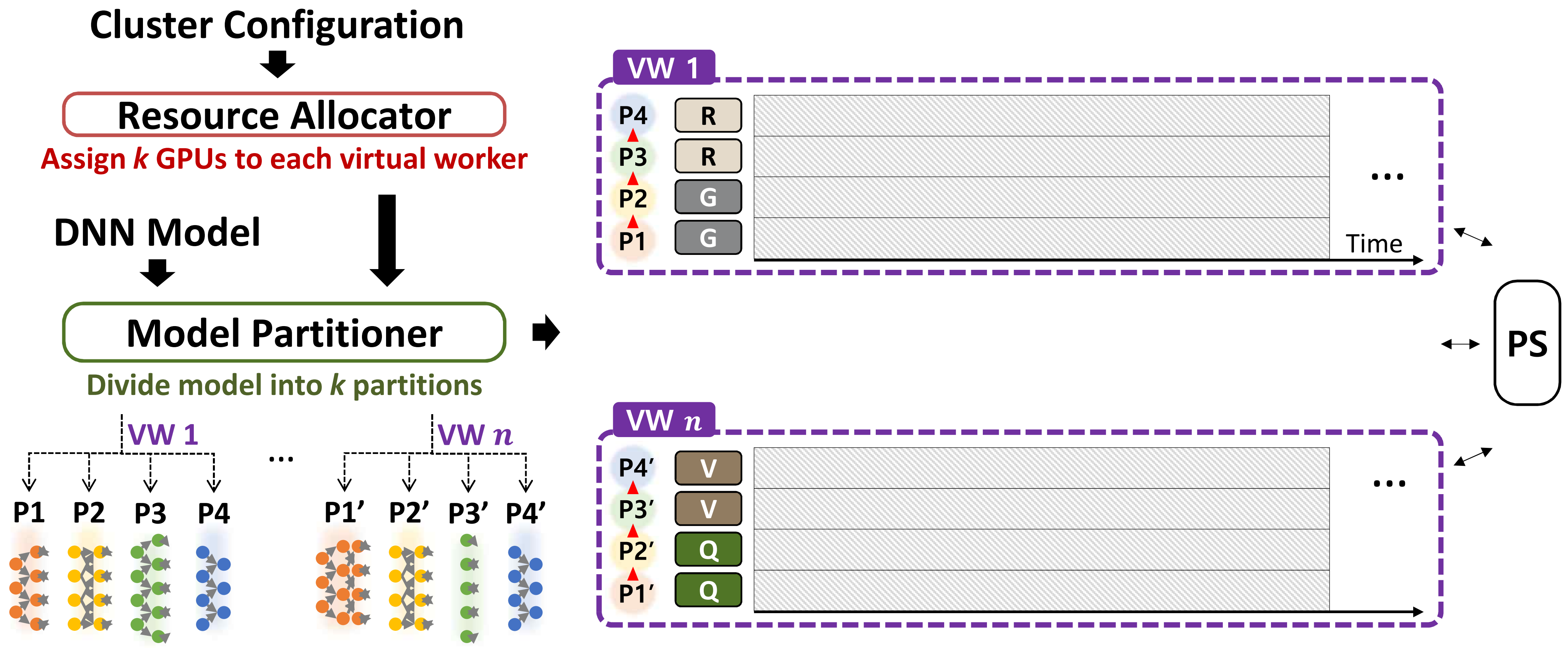
Integrates PMP + DP

Novel parameter synchronization model

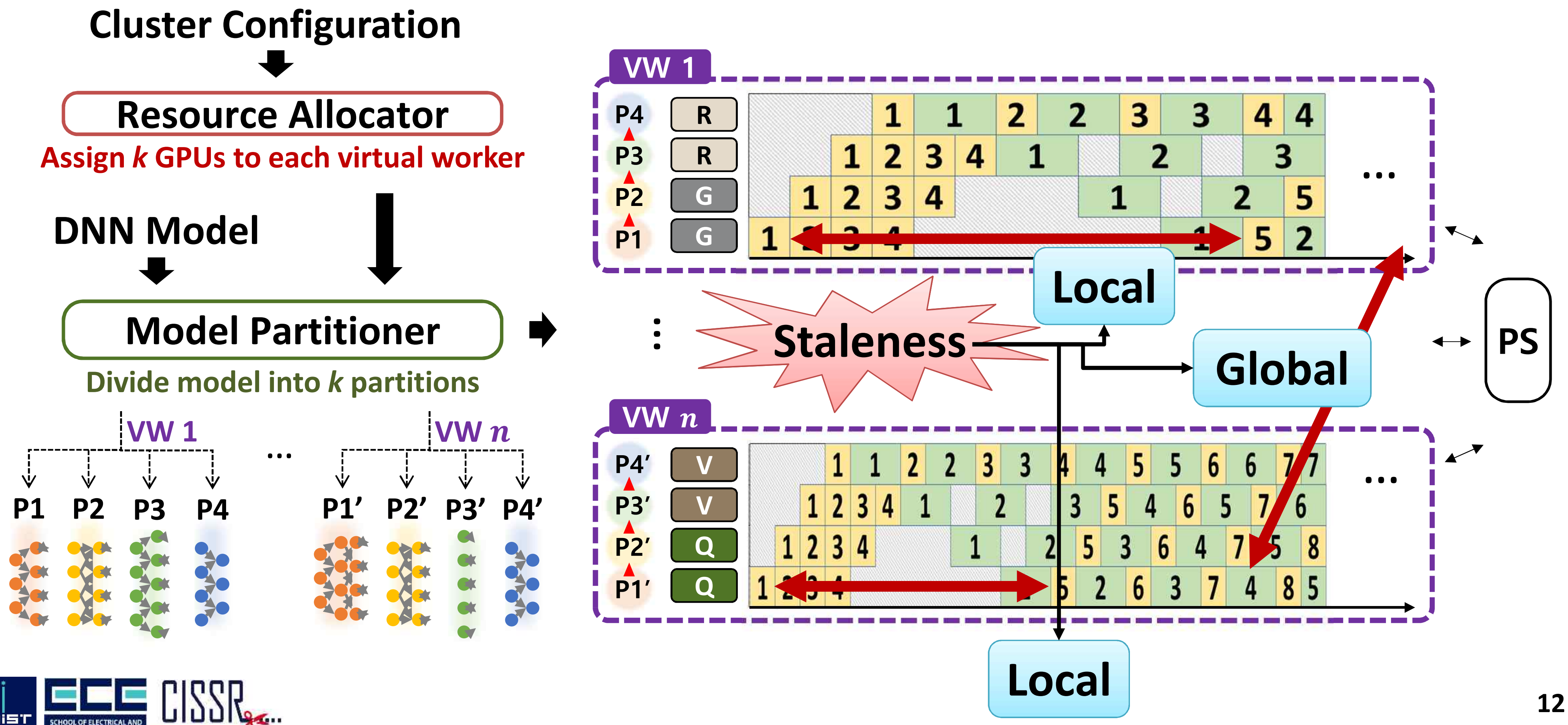
WSP (Wave Synchronous Parallel)

Proof of WSP Convergence

HetPipe Workflow



HetPipe Workflow

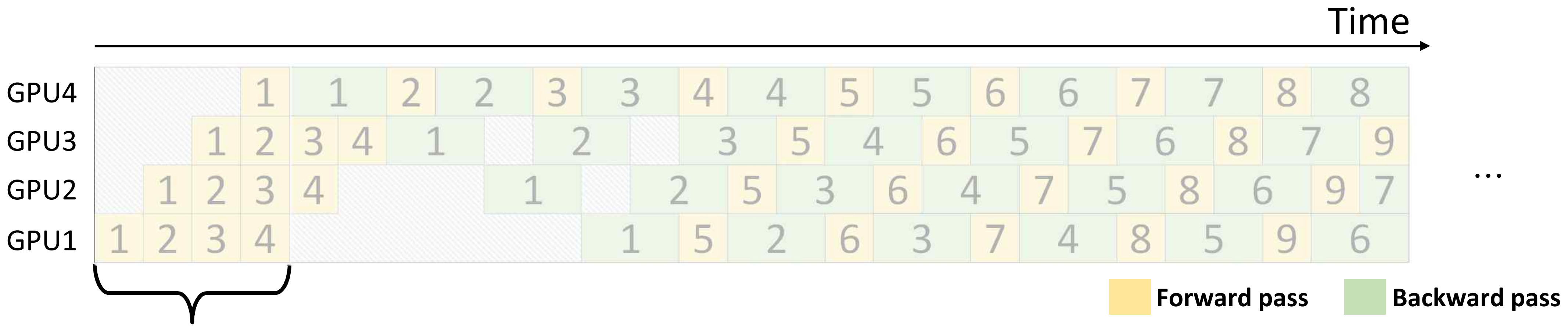


Outline

- Motivation & Background
- HetPipe in a Nutshell
- **Our System: HetPipe**
  - **Pipelined Model Parallelism Within a VW**
  - Data Parallelism with Multiple VWs
- Evaluation
- Conclusion

Pipelined Model Parallelism Within a VW

- **Execution of a virtual worker**



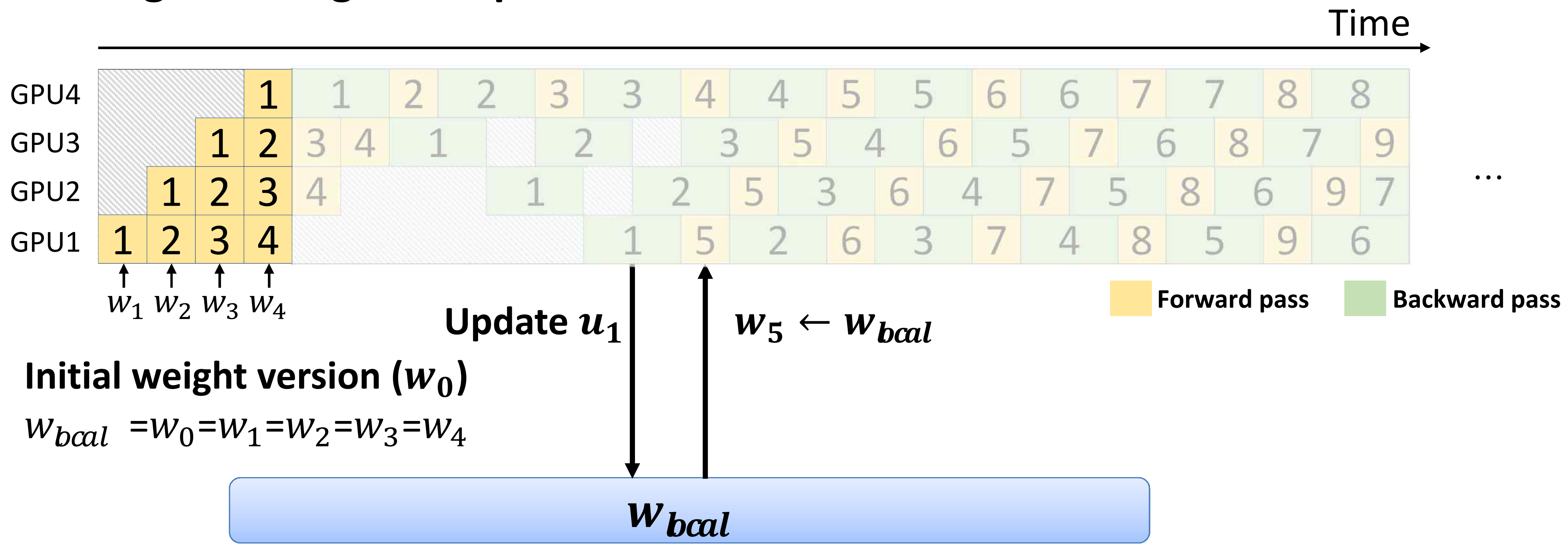
N_m minibatches processed concurrently in pipeline manner

w_{bcal}

W_{bcal} is a consistent version of weights within a VW

Pipelined Model Parallelism Within a VW

- **Weight management procedure**



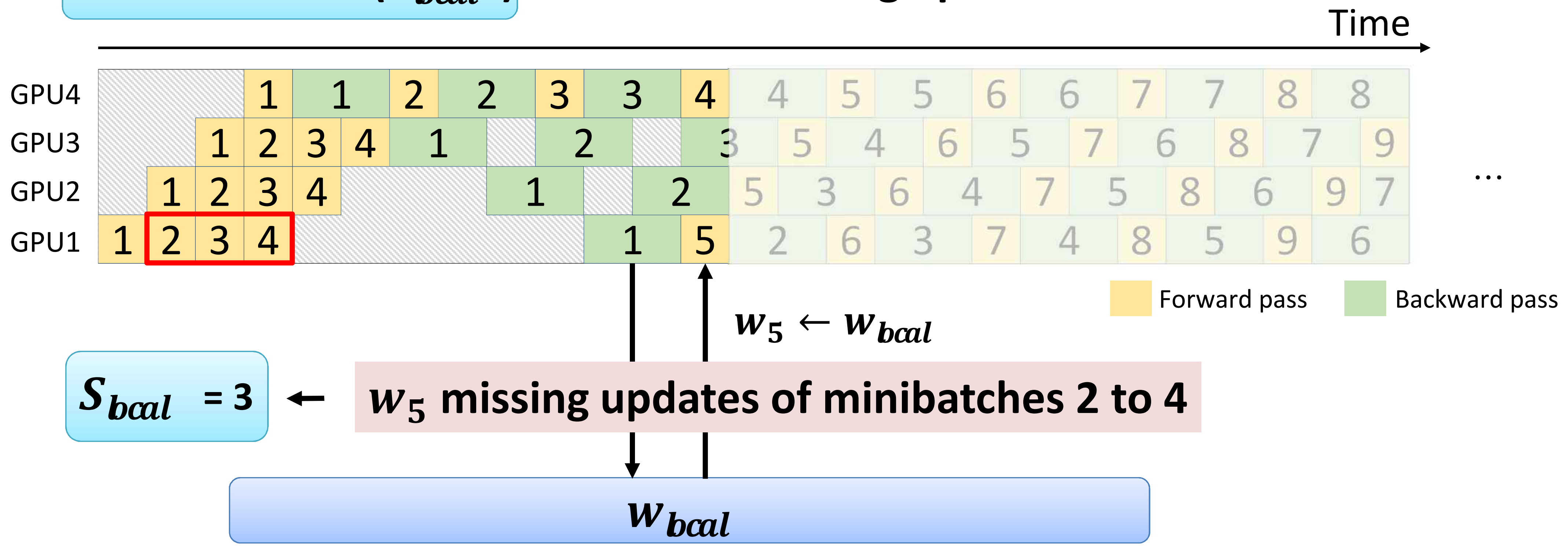
Initial weight version (w_0)

$w_{bcal} = w_0 = w_1 = w_2 = w_3 = w_4$

$$w_{bcal} \leftarrow w_{bcal} + u_1$$

Pipelined Model Parallelism Within a VW

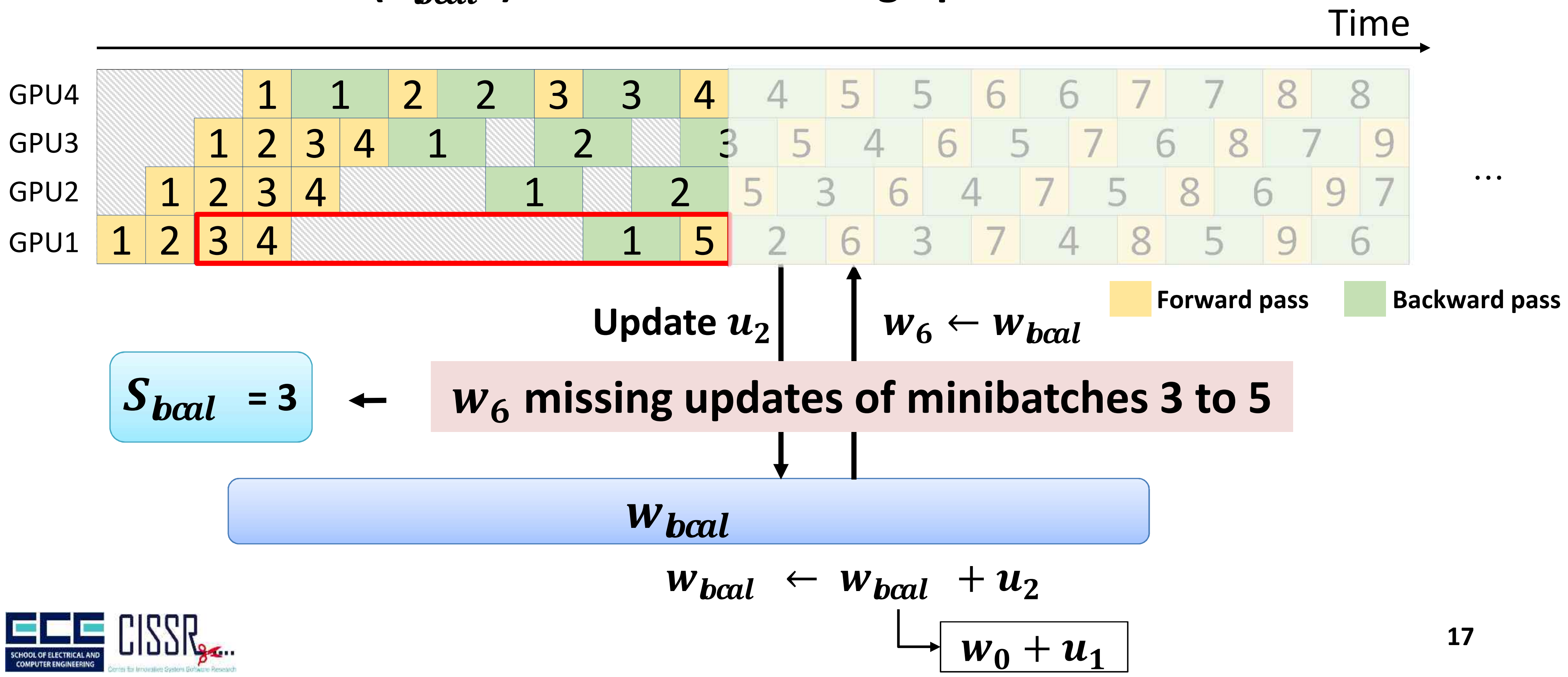
- Local staleness (s_{local}): maximum missing updates



$$w_{local} \leftarrow w_{local} + u_1$$

Pipelined Model Parallelism Within a VW

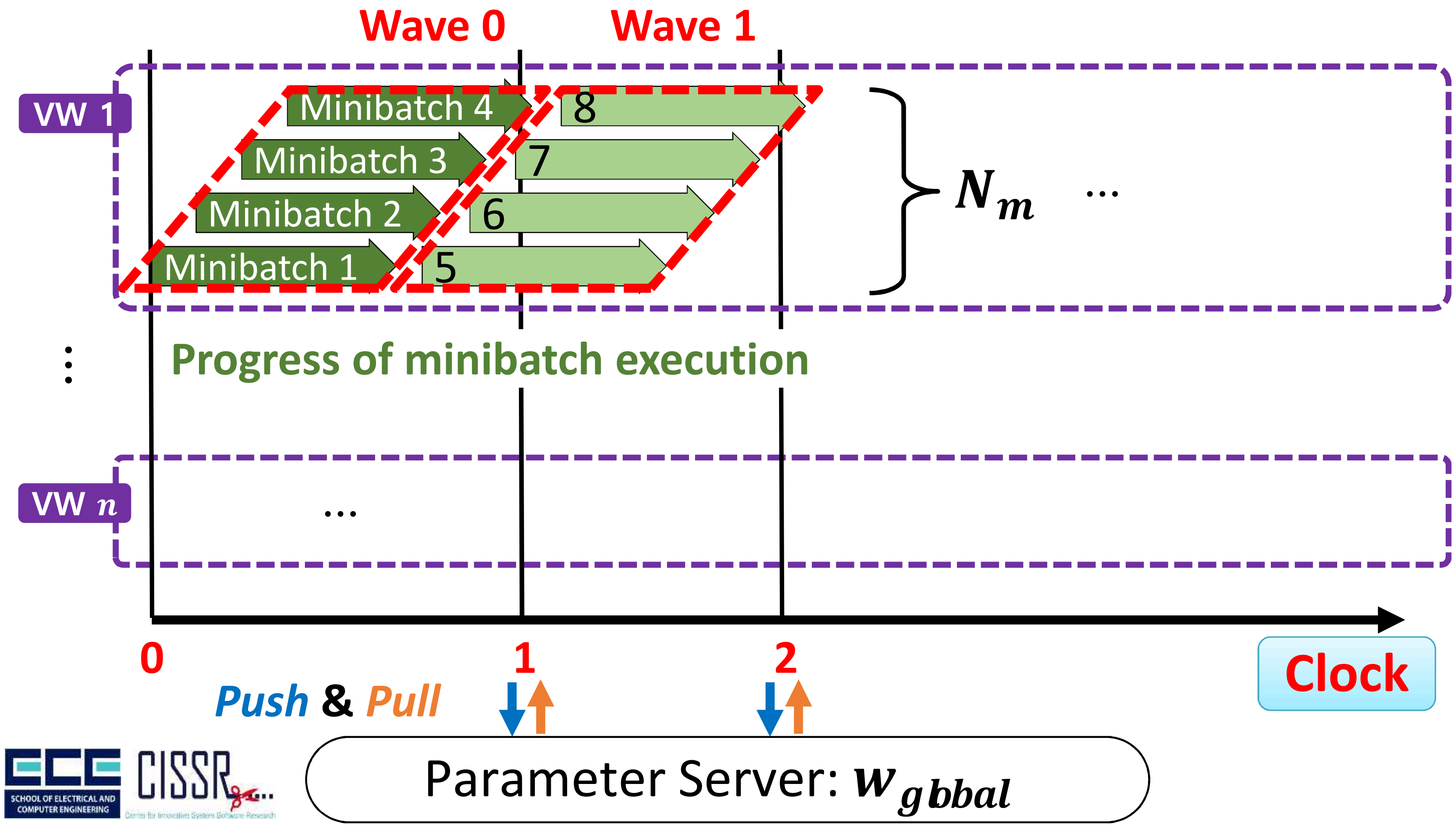
- **Local staleness (S_{local}): maximum missing updates**


Time
GPU4
GPU3
GPU2
GPU1
Forward pass
Backward pass
Update u_2
$w_6 \leftarrow w_{local}$
S_{local} = 3
w_6 missing updates of minibatches 3 to 5
w_{local}
$w_{local} \leftarrow w_{local} + u_2$
$w_0 + u_1$
…

Outline

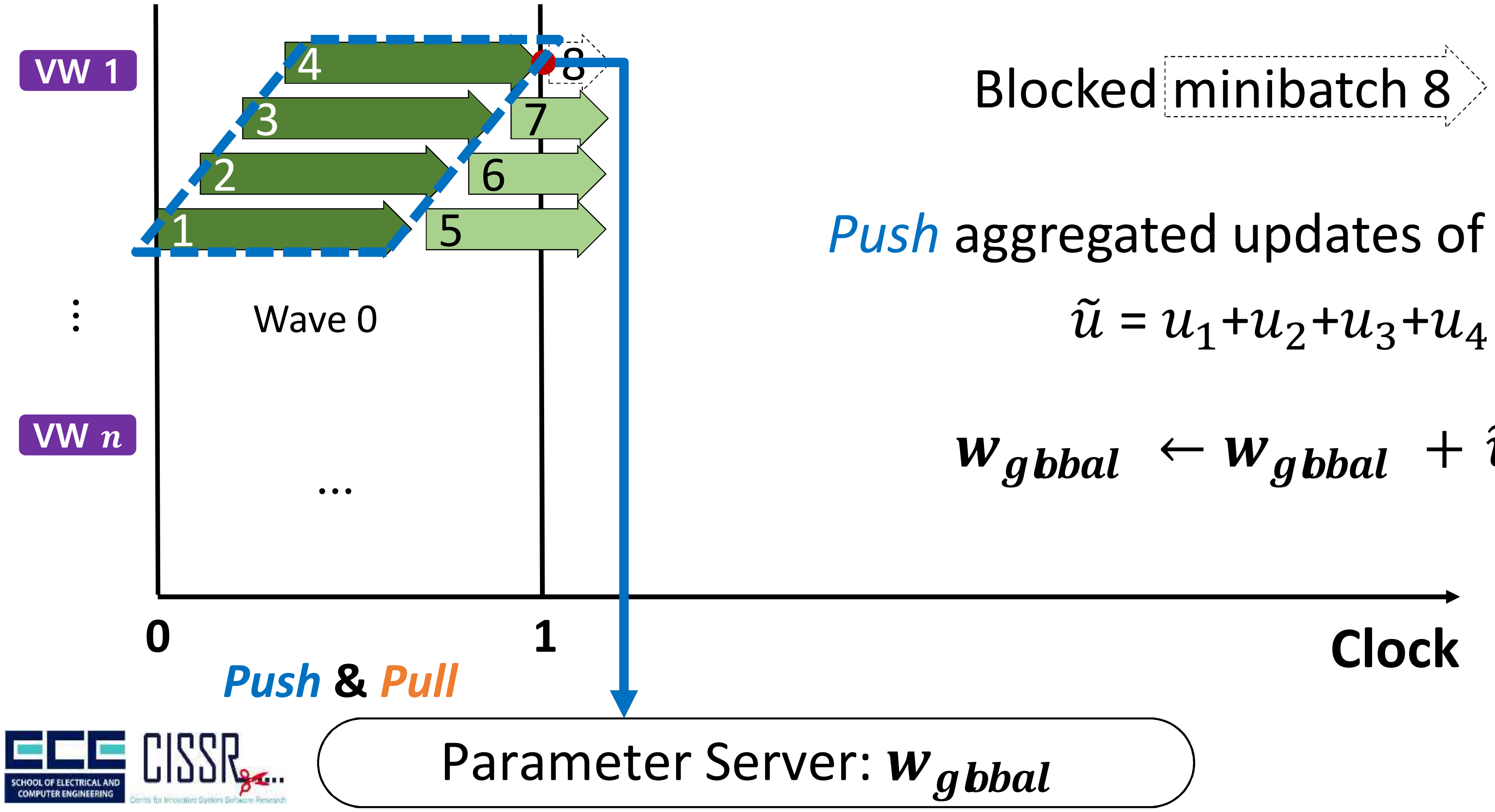
Data Parallelism with Multiple VWs

Wave: Sequence of concurrently executing N_m minibatches



Data Parallelism with Multiple VWs

- *Push* occurs every clock



Blocked minibatch 8

Push aggregated updates of wave0 ($\tilde{u}$)

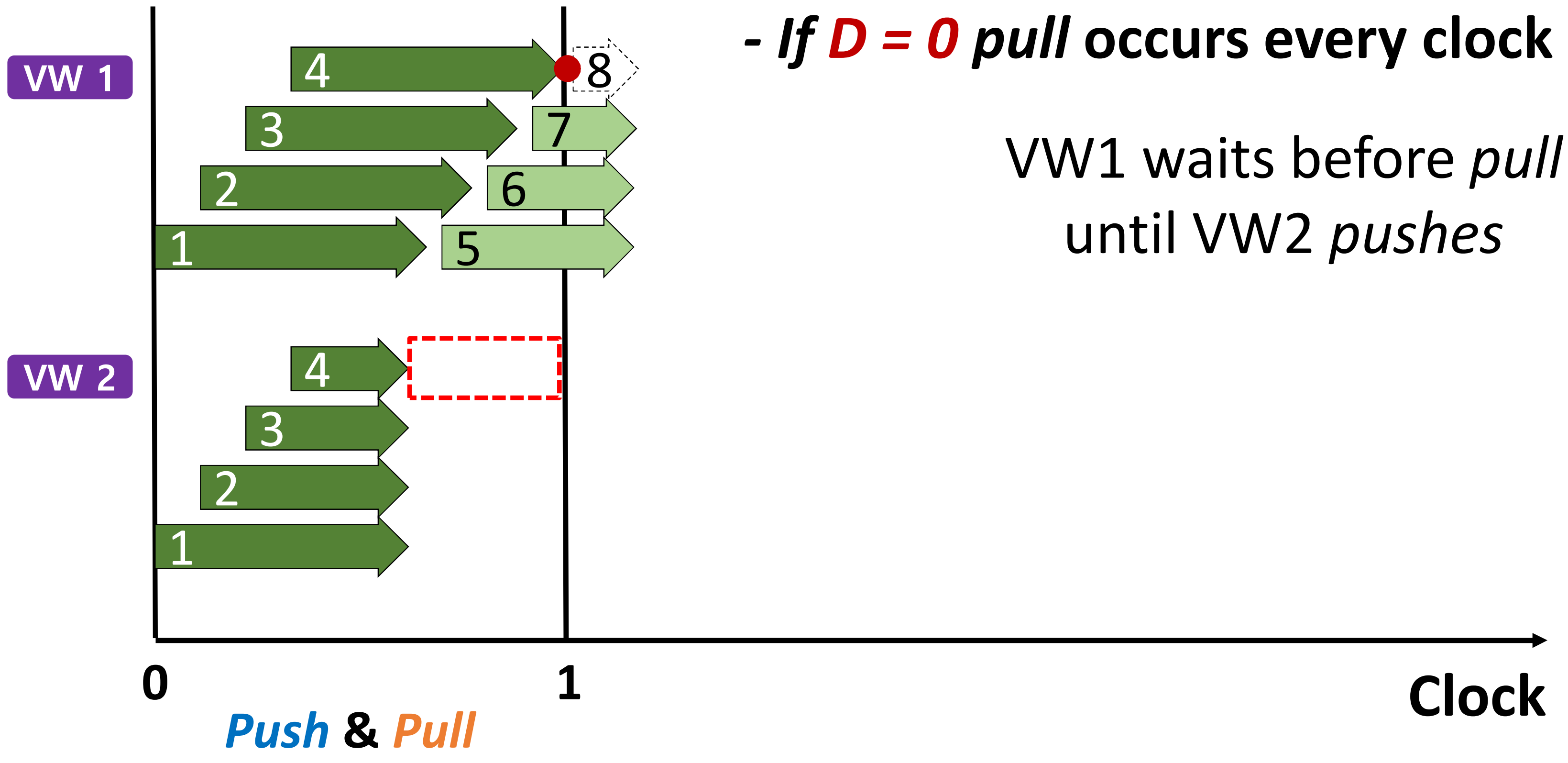
$$\tilde{u} = u_1 + u_2 + u_3 + u_4$$

$$\boldsymbol{w}_{gbbal} \leftarrow \boldsymbol{w}_{gbbal} + \tilde{\boldsymbol{u}}$$

Data Parallelism with Multiple VWs

- ***Pull*** **occurs intermittently - Depending on user defined *clock distance D***

  - *If D = 0 pull* occurs every clock

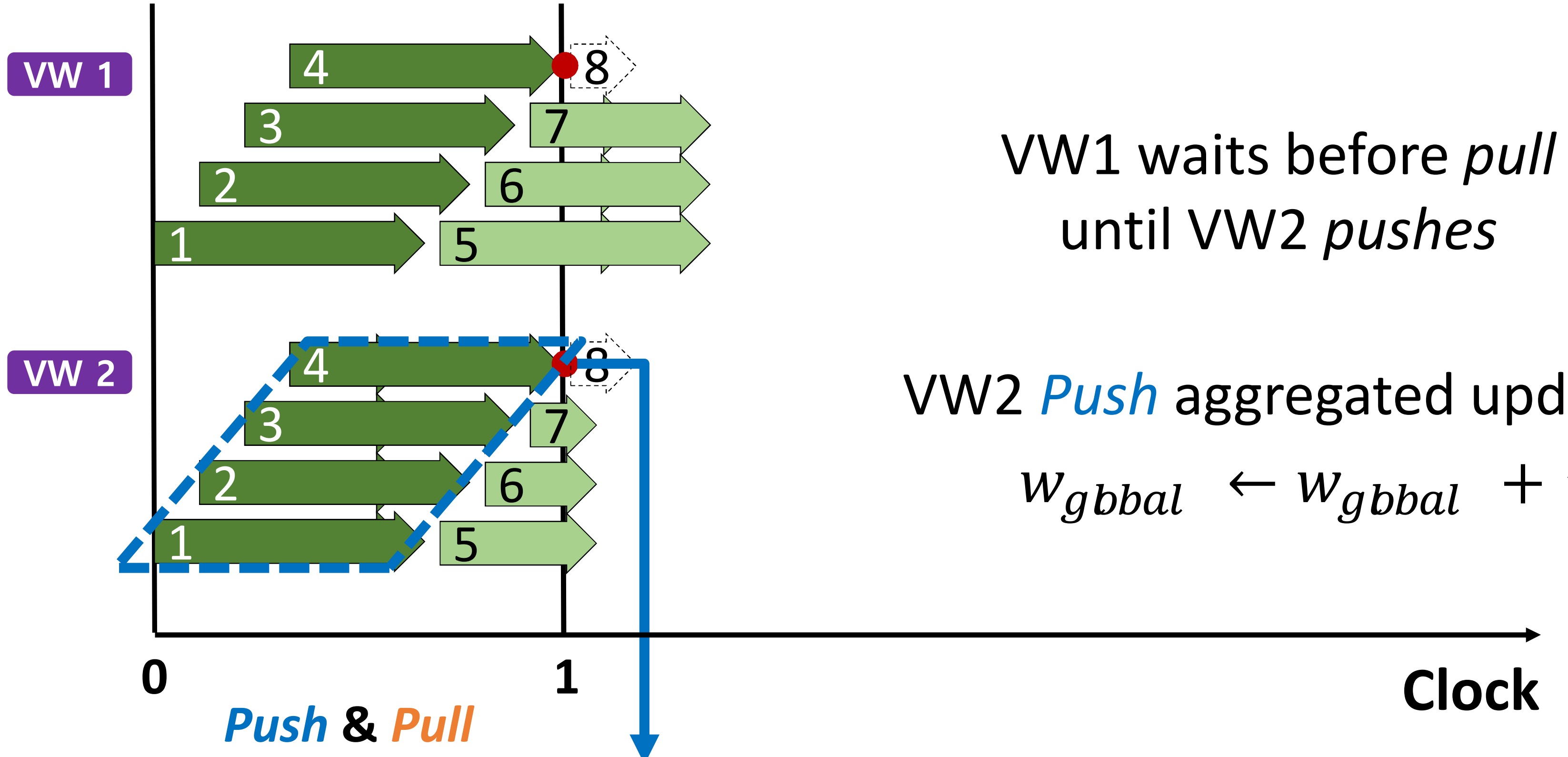


VW1 waits before *pull* until VW2 *pushes*

Parameter Server: $\boldsymbol{w}_{global}$

Data Parallelism with Multiple VWs

- *Pull* occurs intermittently - Depending on user defined *clock distance D*



If D = 0

VW1 waits before *pull* until VW2 *pushes*

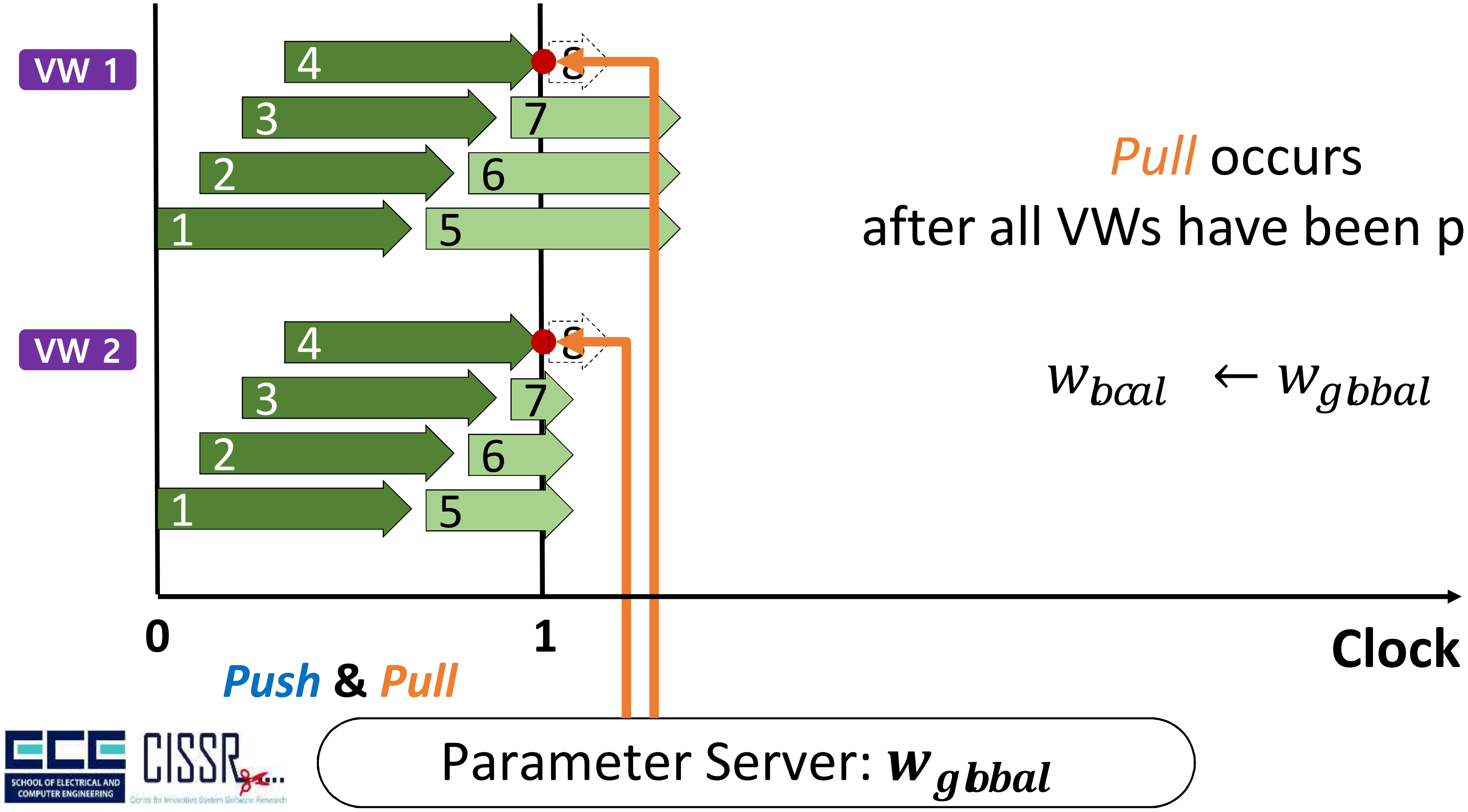
VW2 *Push* aggregated updates ($\tilde{u}$)

$$w_{global} \leftarrow w_{global} + \tilde{u}$$

Parameter Server: $\boldsymbol{w}_{\boldsymbol{global}}$

Data Parallelism with Multiple VWs

- *Pull* occurs intermittently - Depending on user defined *clock distance D*



Parameter Server: w_{global}

If D = 0

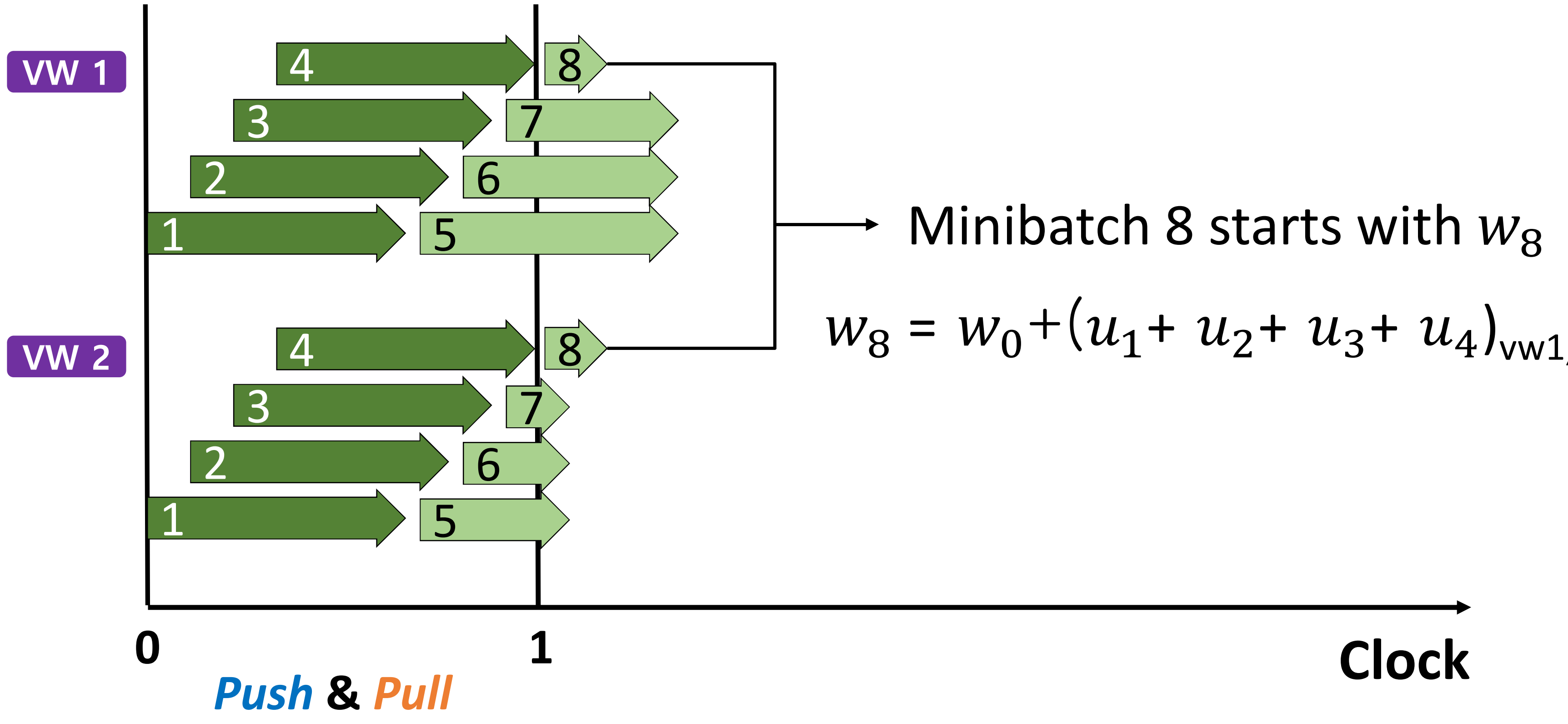
Pull occurs
after all VWs have been pushed

$w_{local} \leftarrow w_{global}$

Data Parallelism with Multiple VWs

- *Pull* occurs intermittently - Depending on user defined *clock distance D*

If D = 0



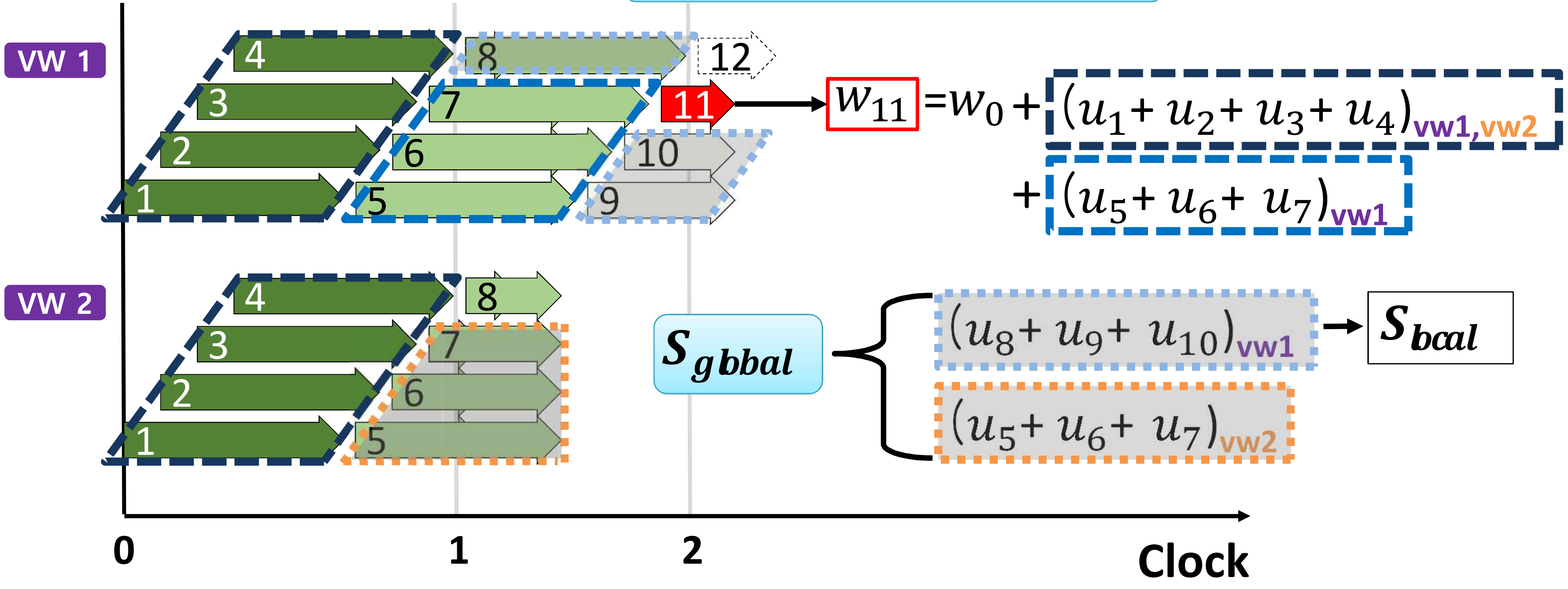
Minibatch 8 starts with w_8

$$w_8 = w_0 + (u_1 + u_2 + u_3 + u_4)_{vw1,vw2}$$

Parameter Server: $\boldsymbol{w}_{global}$

Data Parallelism with Multiple VWs

- Local staleness (S_{local}) and global staleness (S_{global}) with WSP



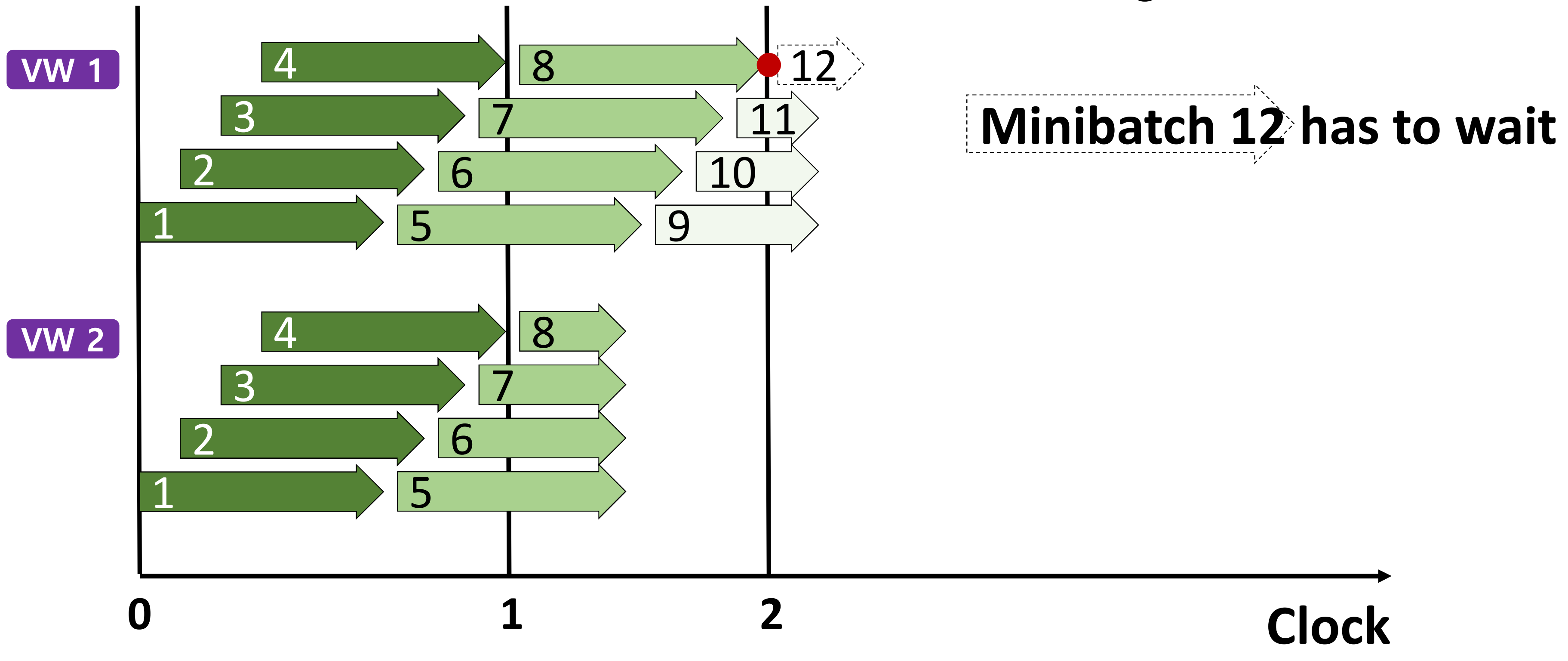
$$w_{11} = w_0 + (u_1 + u_2 + u_3 + u_4)_{vw1,vw2} + (u_5 + u_6 + u_7)_{vw1}$$

$$S_{global} \begin{cases} (u_8 + u_9 + u_{10})_{vw1} \rightarrow S_{local} \\ (u_5 + u_6 + u_7)_{vw2} \end{cases}$$

$$w_{global} = w_0 + (u_1 + u_2 + u_3 + u_4)_{vw1,vw2}$$

Data Parallelism with Multiple VWs

- **Local staleness (S_{local}) and global staleness (S_{global}) with WSP**



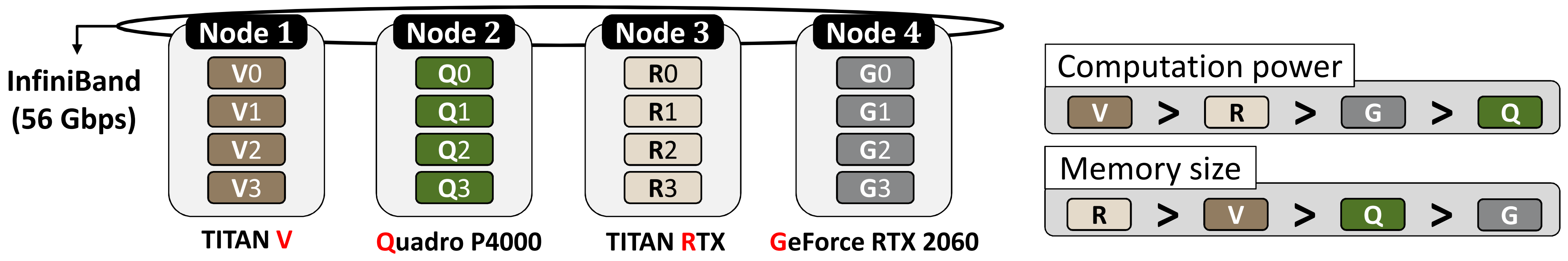
Parameter Server: w_{global}

Outline

- Motivation & Background
- HetPipe in a Nutshell
- Our System: HetPipe
- **Evaluation**
  - **Setup**
  - **Resource Allocation for Virtual Workers**
  - **Results**
- Conclusion

Evaluation Setup

- **Cluster setup - 4 heterogeneous GPU nodes**

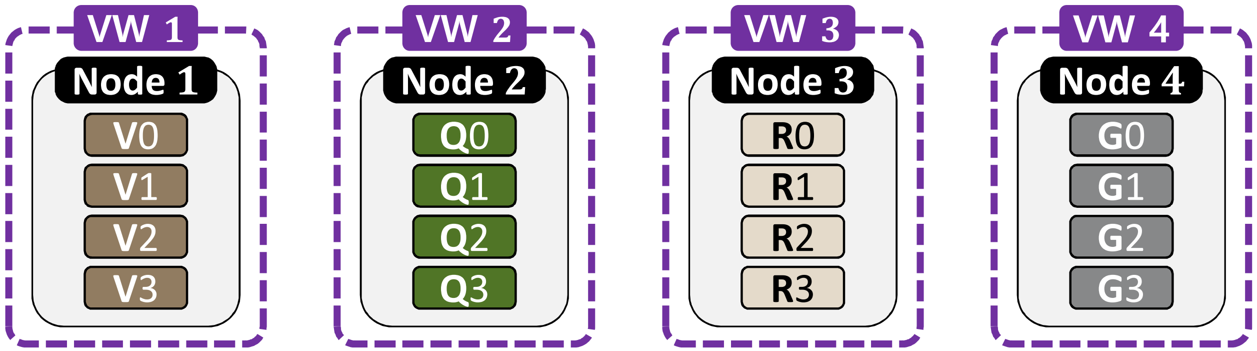


- **Two DNN models**

	ResNet-152	**VGG-19**
Dataset, minibatch size	ImageNet, 32	
Model parameter size	230 MB	548 MB
Characteristic	Large activation output	Large parameter size

Resource Allocation for Virtual Workers: NP, ED, HD

- NP (Node Partition)

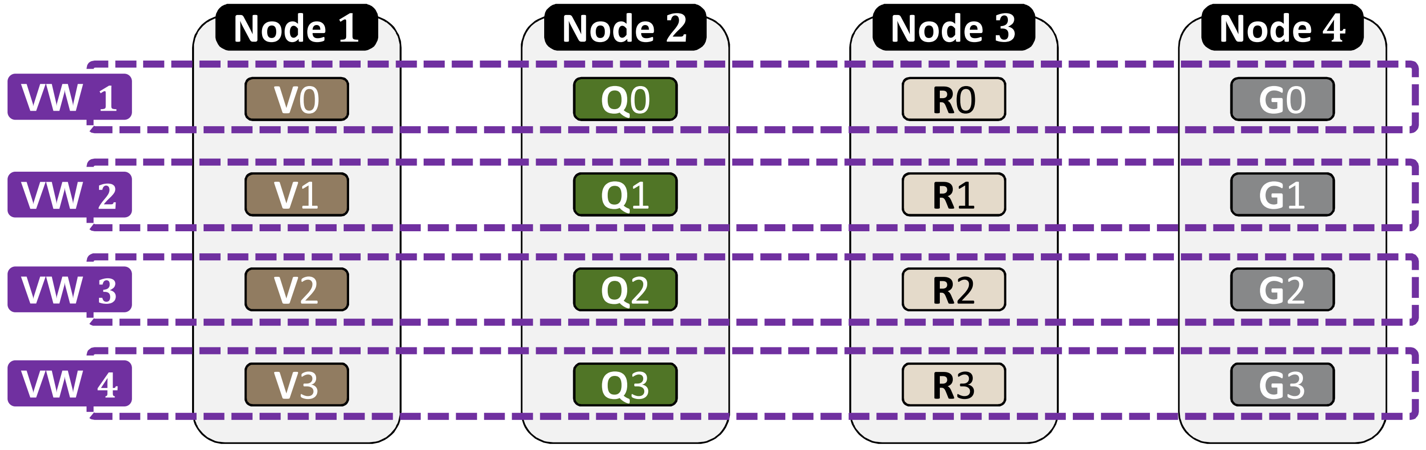


- Minimum communication overhead within VW

- Performance of each virtual worker varies
- Straggler may degrade performance with DP

Resource Allocation for Virtual Workers: NP, ED, HD

- ED (Equal Distribution)

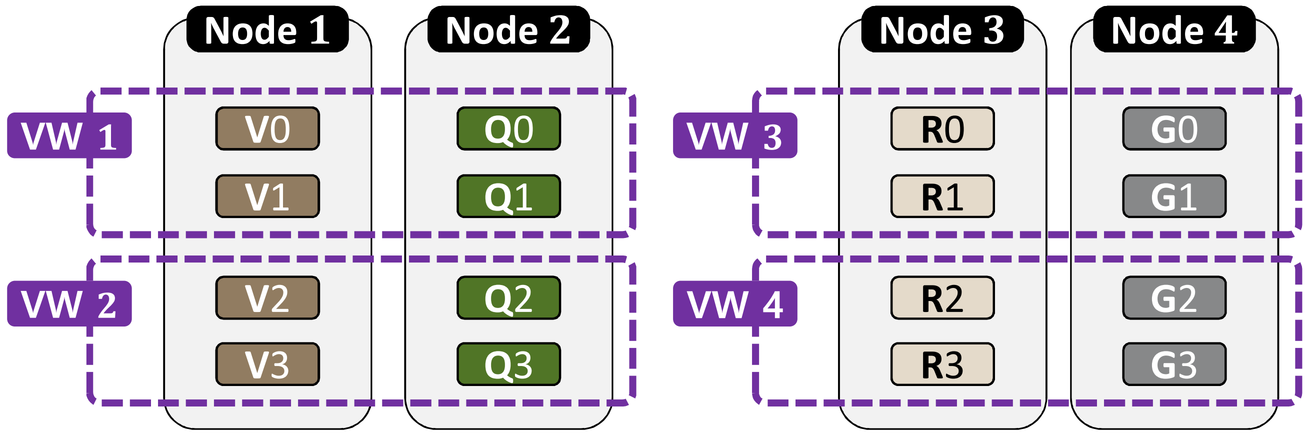


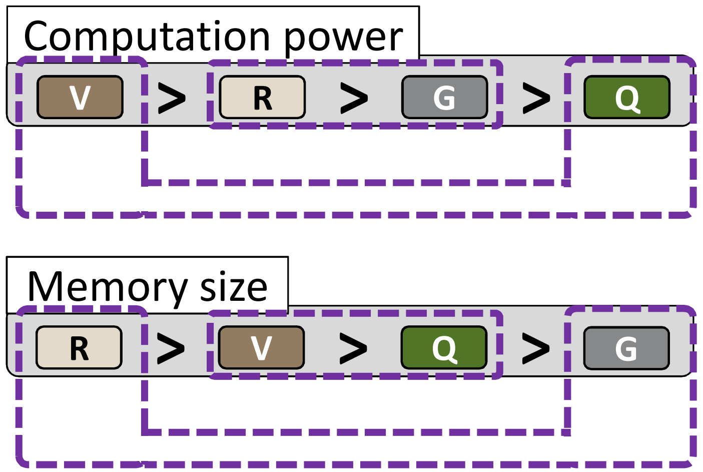
- Performance will be the same across the VWs
- Mitigates the straggler problem

- High communication overhead within each VW

Resource Allocation for Virtual Workers: NP, ED, HD

- HD (Hybrid Distribution)





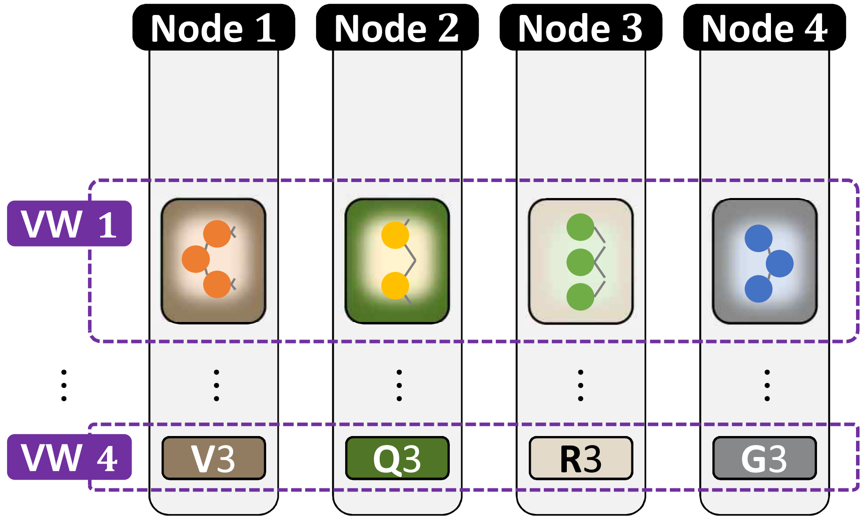
- Mitigates the straggler problem
- Reduces communication overhead within each VW

Parameter Placement

- **Round-robin policy (default)**
  - Can be used in all three policies: **NP**, **ED**, and **HD**

Parameters of each layer:

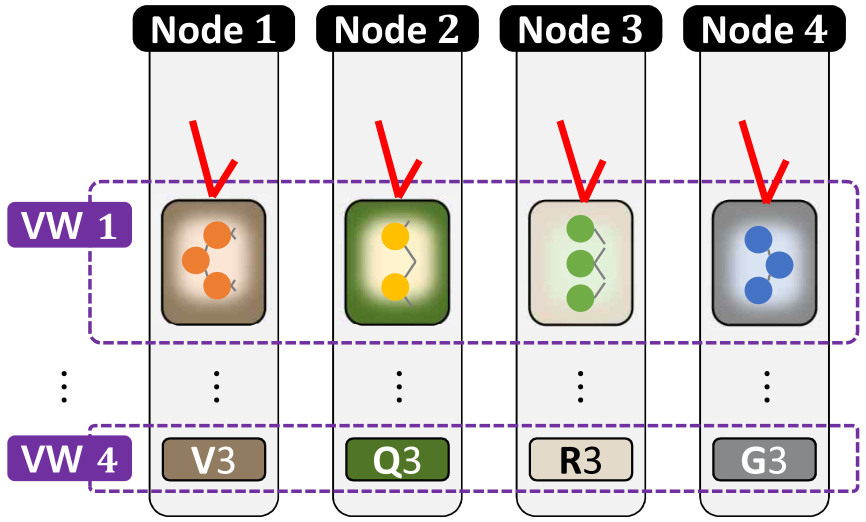
Example: ED



Parameter Placement

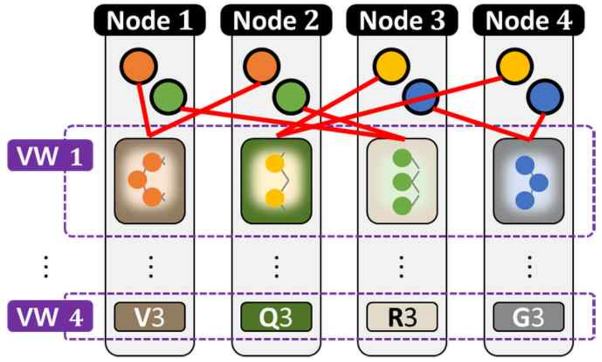
- Local placement policy
  - ED-local

Parameters of each layer:



- Significantly reduces communication overhead

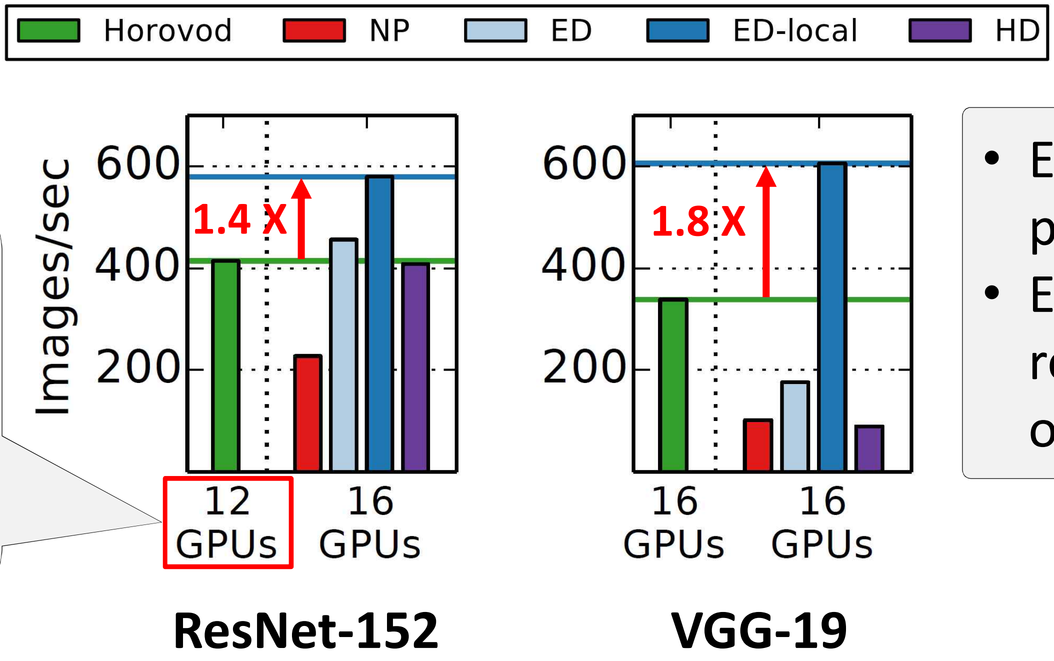
ED



- Parameter communication occurs

Compare Throughput with Horovod

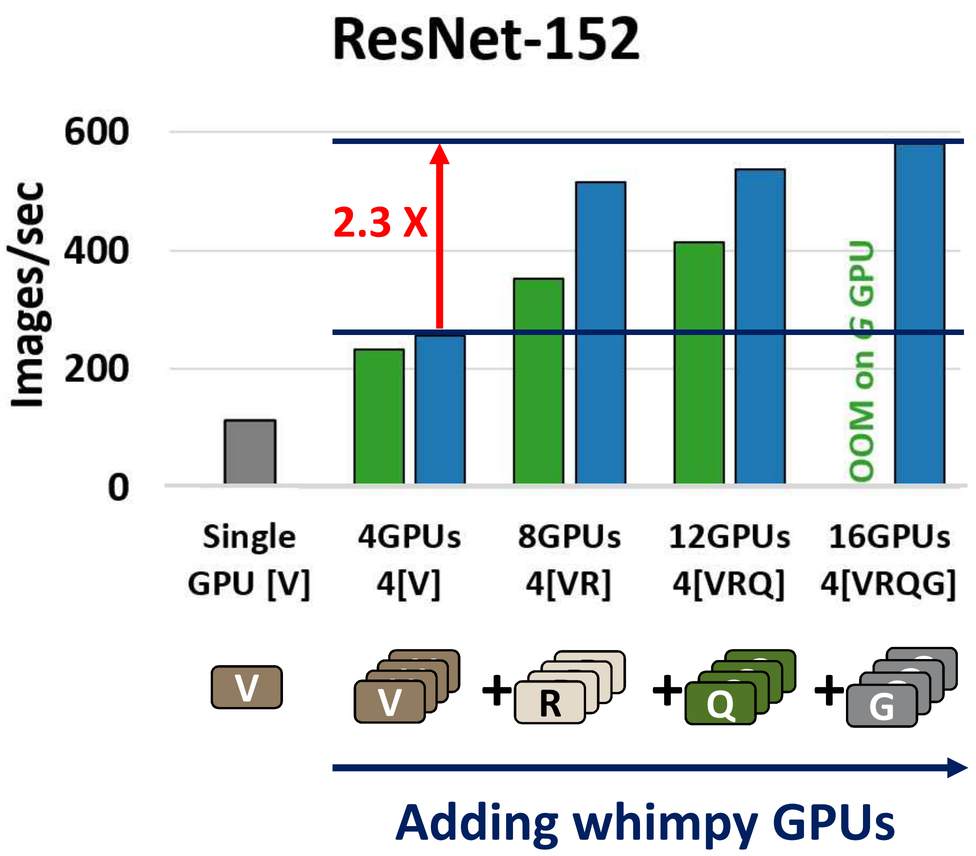
- **Baseline Horovod**
  - State-of-the-art DP using AllReduce



- For ResNet-152, the whole model is too large to be loaded into a single ***G*** type GPU (batch size = 32)

- ED: reduces the straggler problem
- ED-local: significantly reduces communication overhead

Performance Improvement of Adding Whimpy GPUs



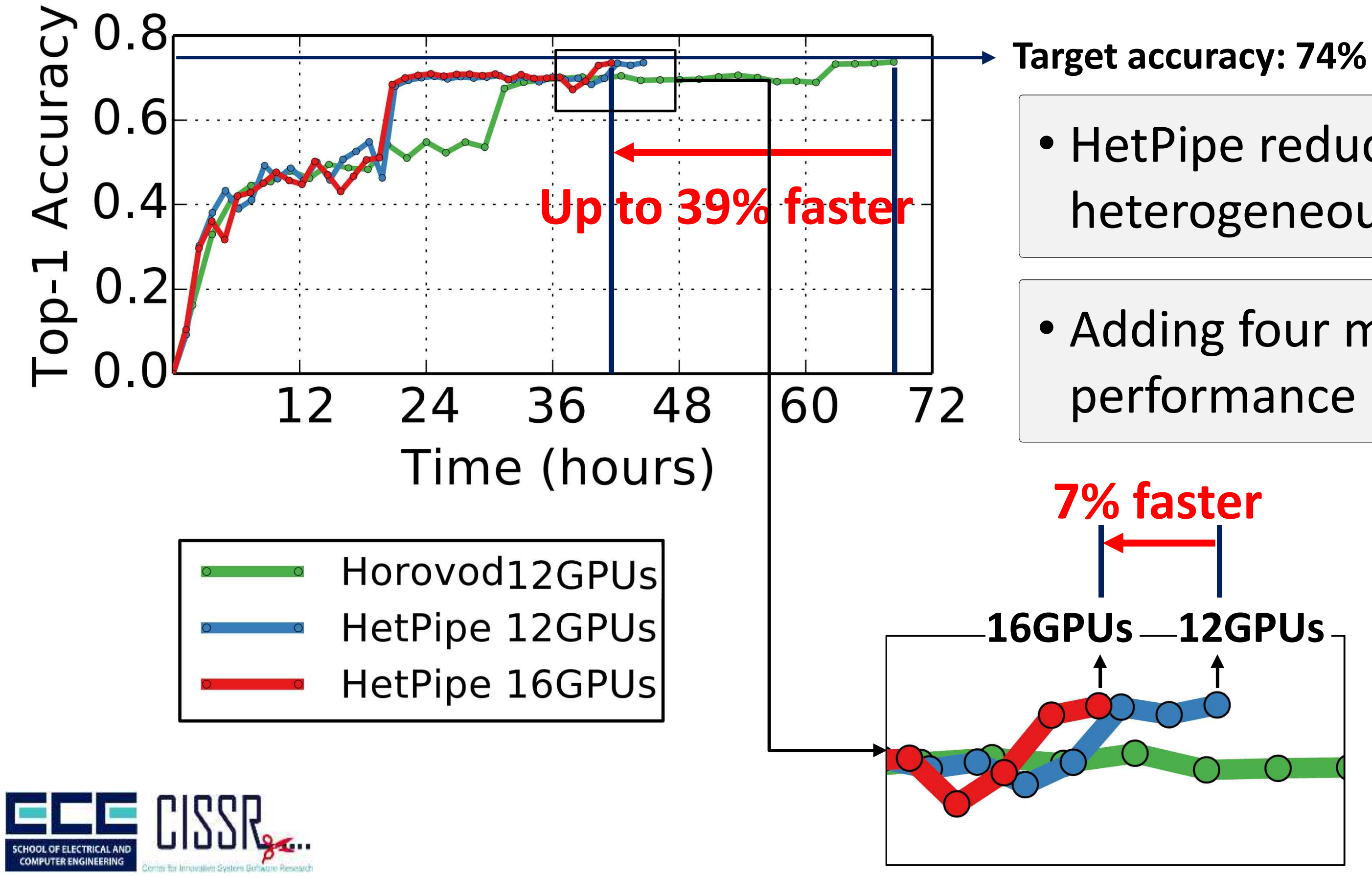
⬛ Single GPU 🟩 Horovod 🟦 HetPipe

- With additional GPUs, HetPipe achieves up to 2.3X speed up

- Additional whimpy systems allow for faster training

Convergence Results

- **ResNet-152**

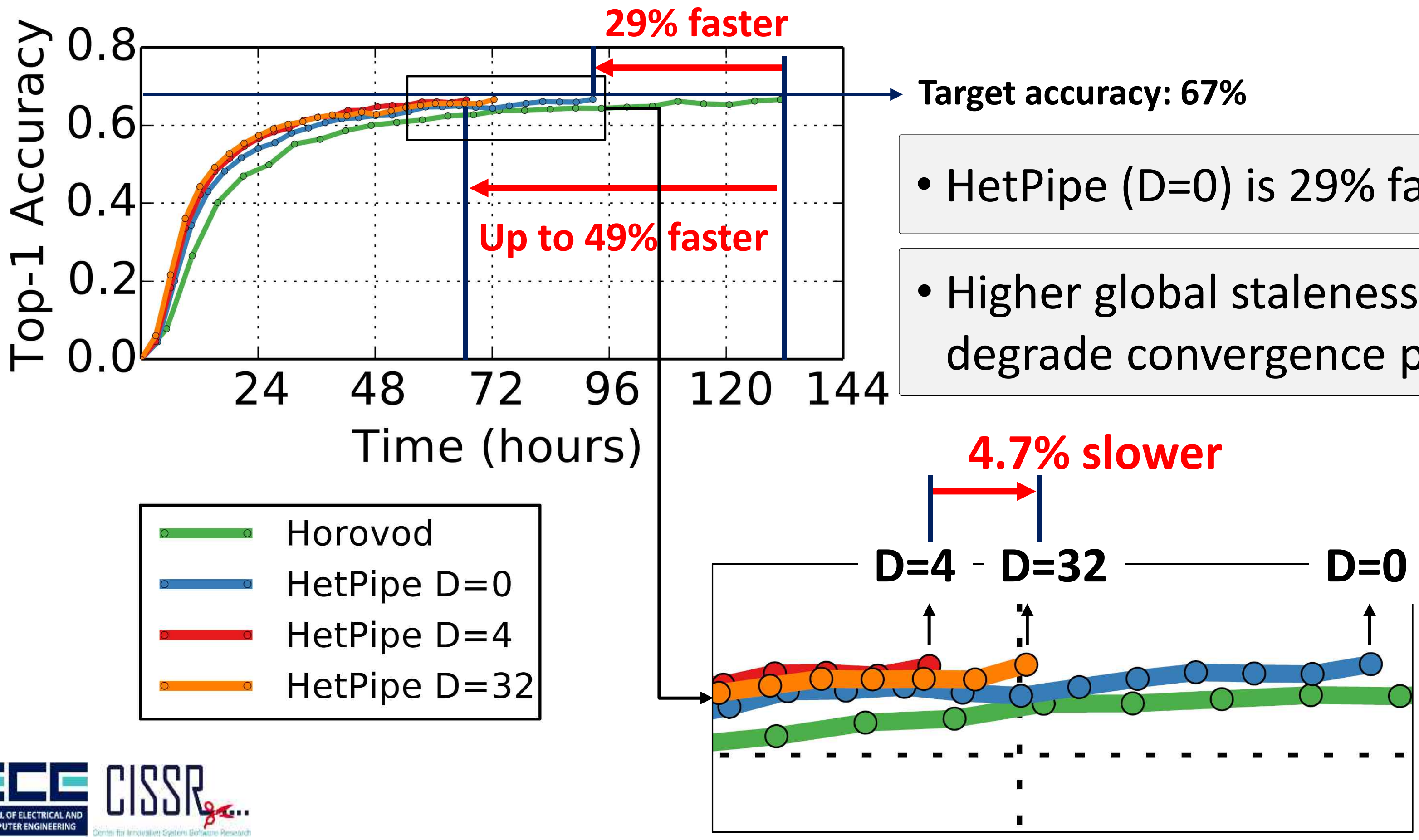


- HetPipe reduces straggler problem in heterogeneous environment

- Adding four more whimpy *G* GPUs, performance improves even more

Convergence Results

- **VGG-19**



- HetPipe (D=0) is 29% faster than Horovod

- Higher global staleness (i.e., 32) can degrade convergence performance

Conclusion

- HetPipe makes it possible to efficiently **train large DNN models with heterogeneous GPUs**
- **Integrate pipelined model parallelism with data parallelism**
- Propose a novel parameter synchronization model: **WSP**
- DNN models converge up to **49% faster with HetPipe**

Thank you!

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