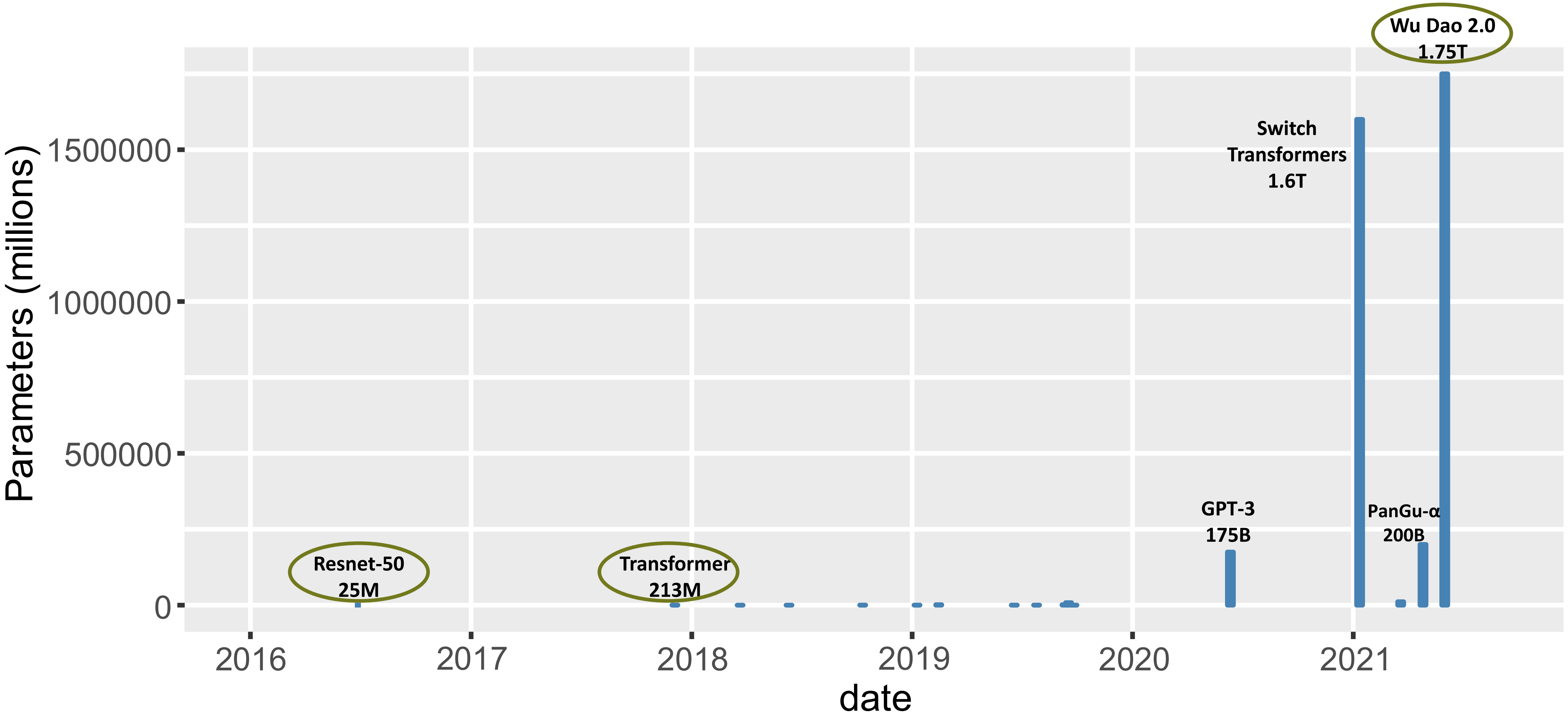
Chimera: Efficiently Training Large-Scale Neural Networks with Bidirectional Pipelines

Shigang Li, Torsten Hoefler
SPCL Lab, ETH Zurich

Model size growing rapidly



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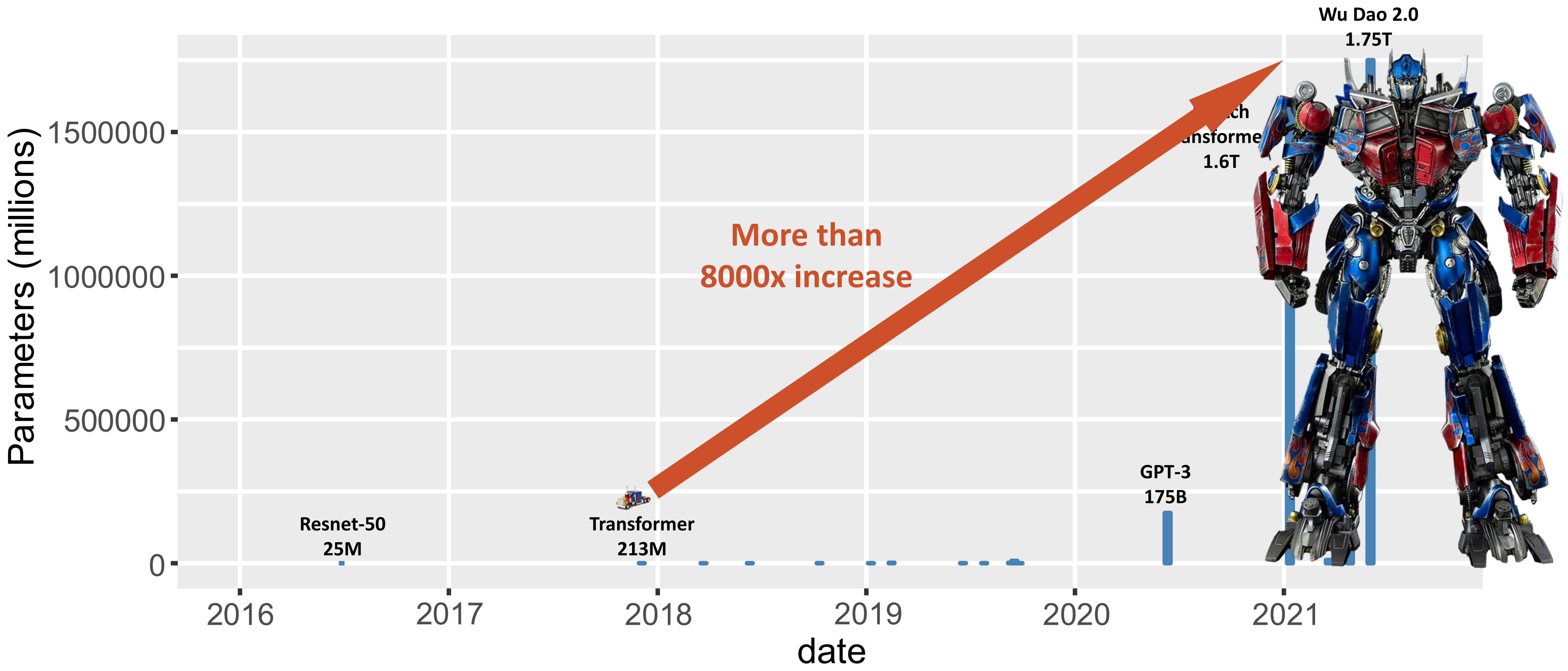

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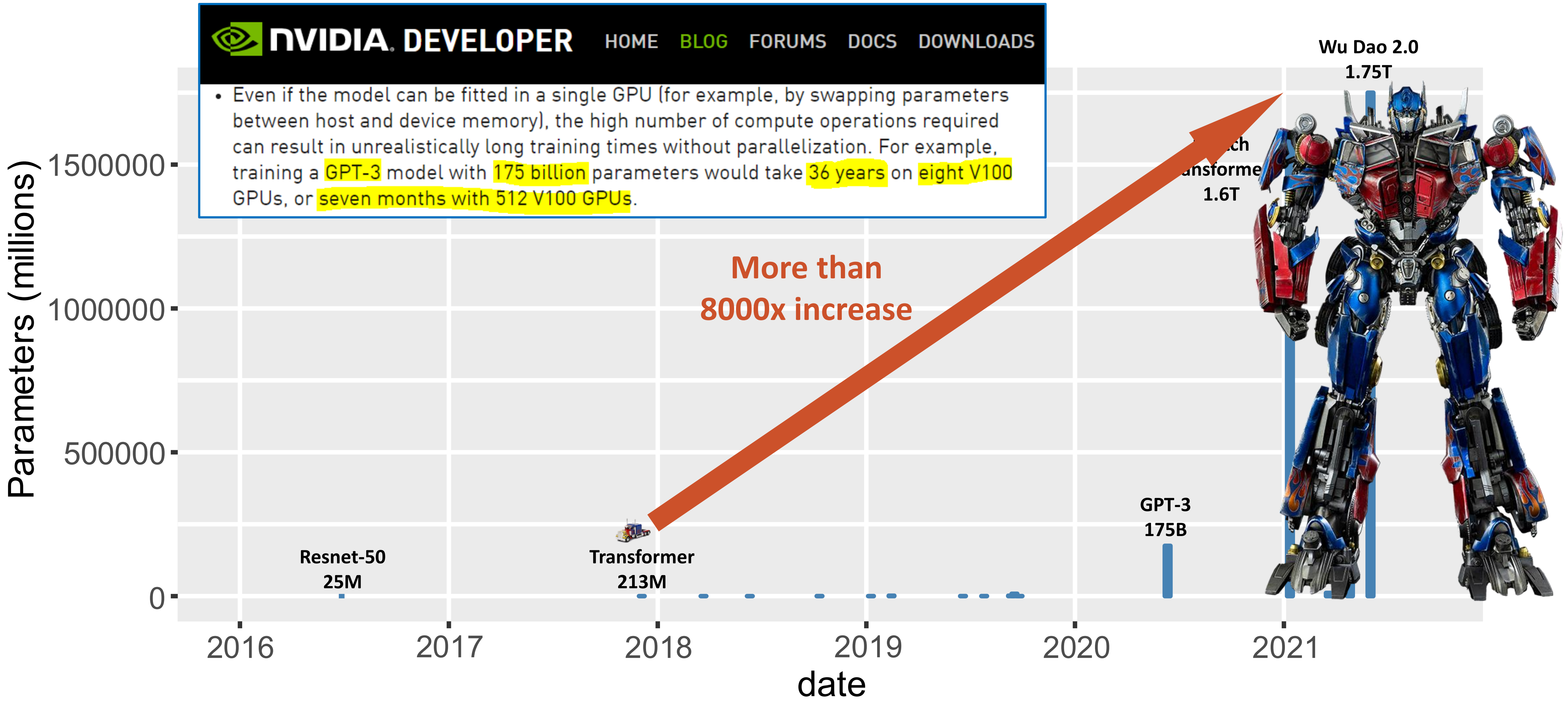
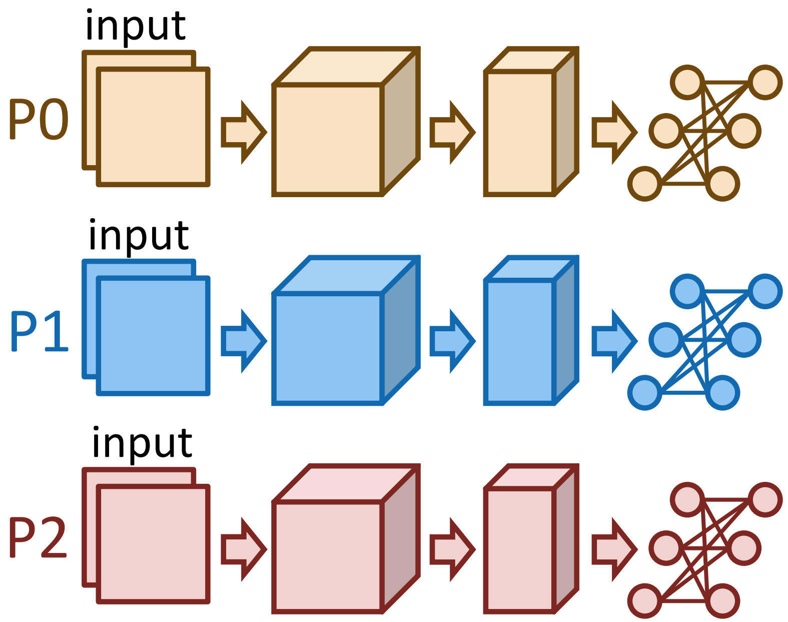


Parallel and distributed training

Data parallelism



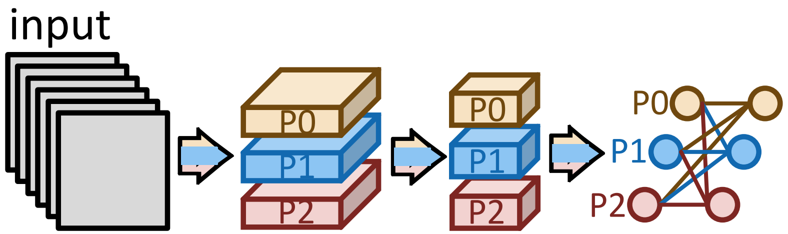
Pros:

a. Easy to realize

Cons:

a. Not work for large models
b. High allreduce overhead

Operator parallelism



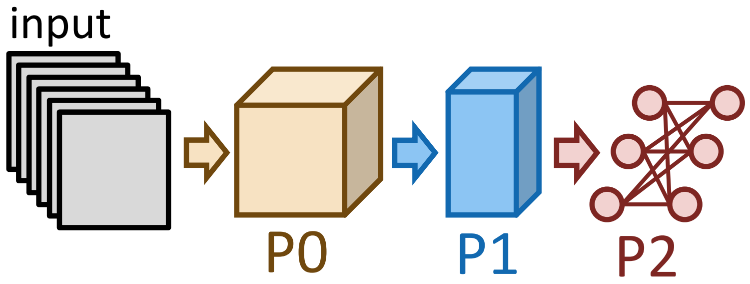
Pros:

a. Make large model training feasible

Cons:

b. Communication for each operator (or each layer)

Pipeline parallelism



Pros:

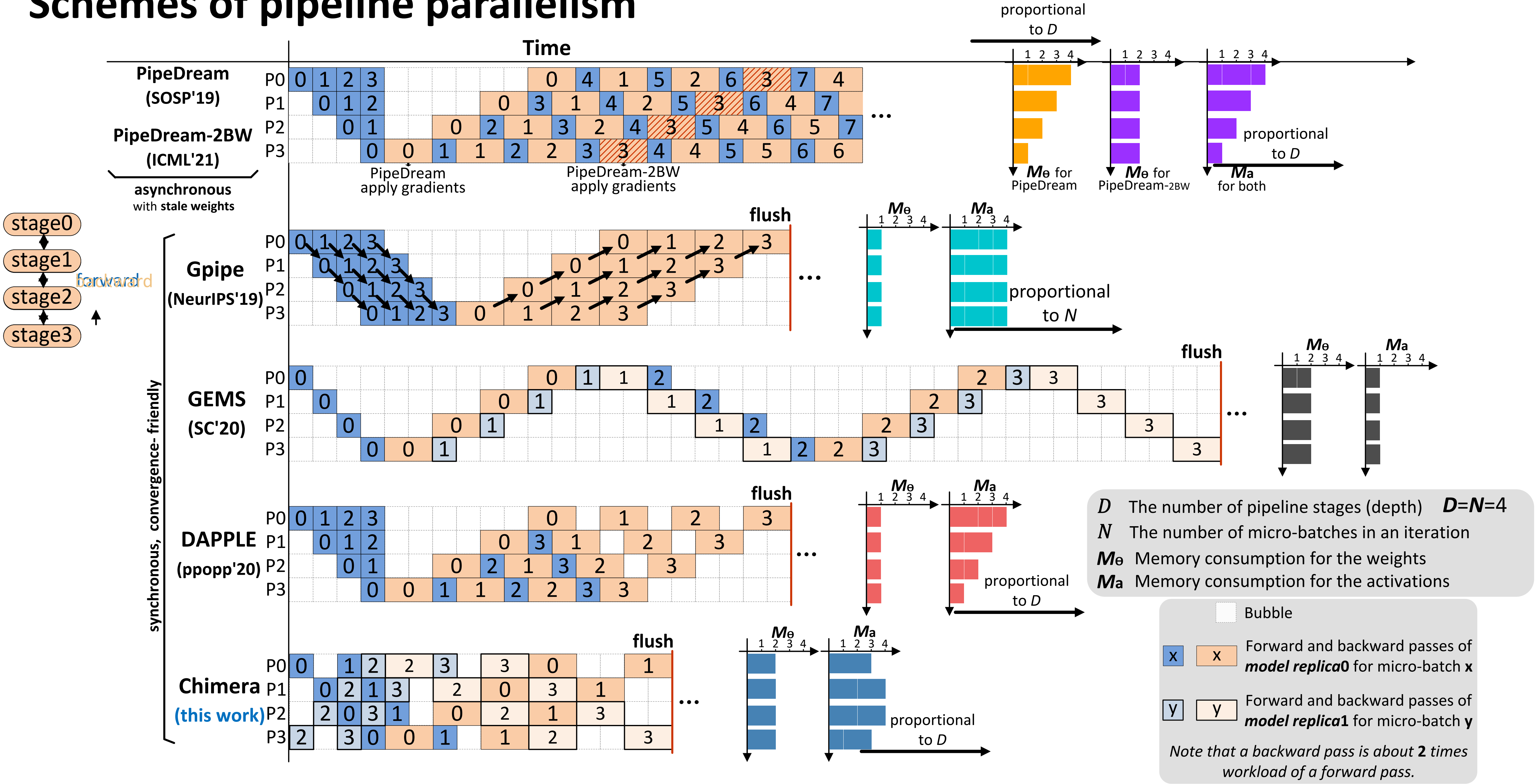
a. Make large model training feasible
b. No collective, only P2P between stages

Cons:

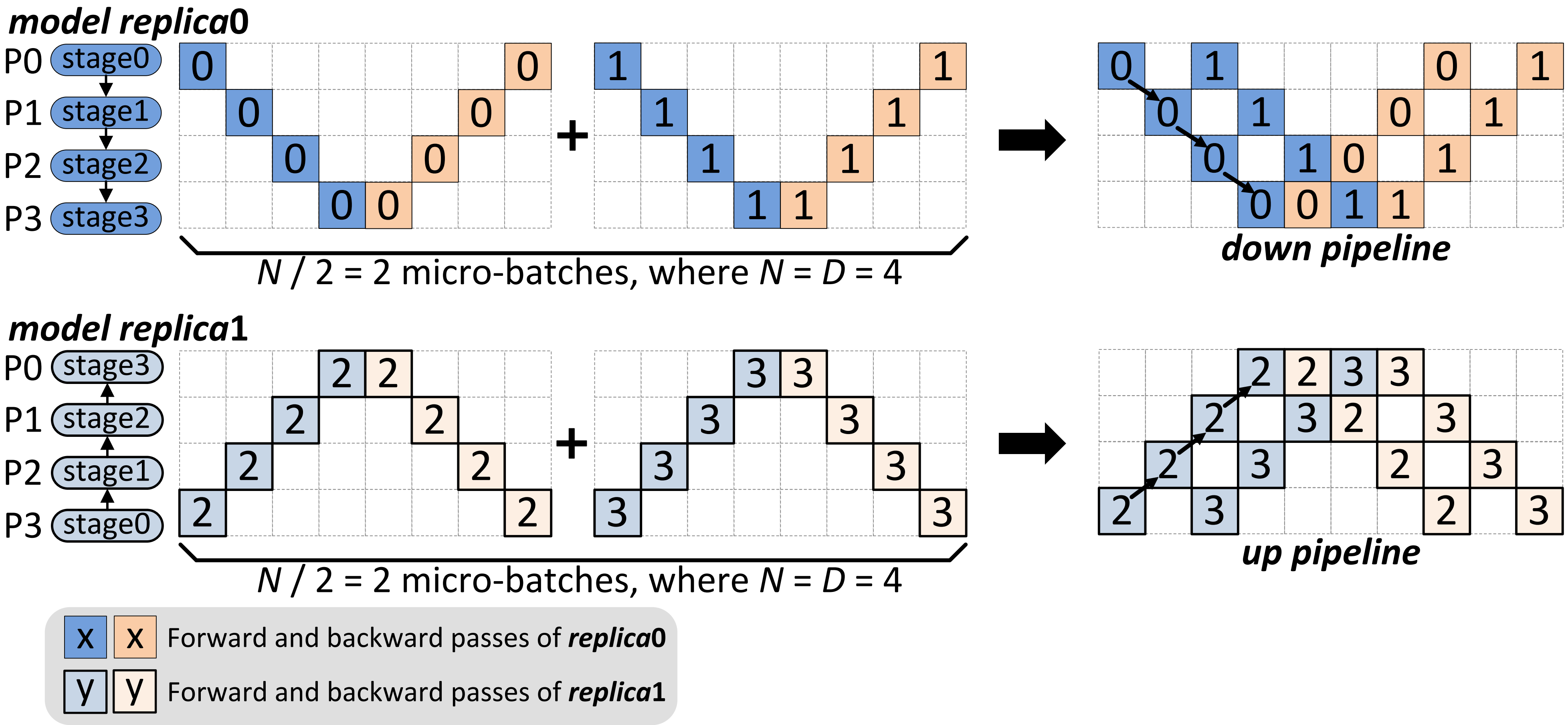
a. Bubbles in pipeline
b. Removing bubbles leads to stale weights

Chimera (this work) aims to solve.

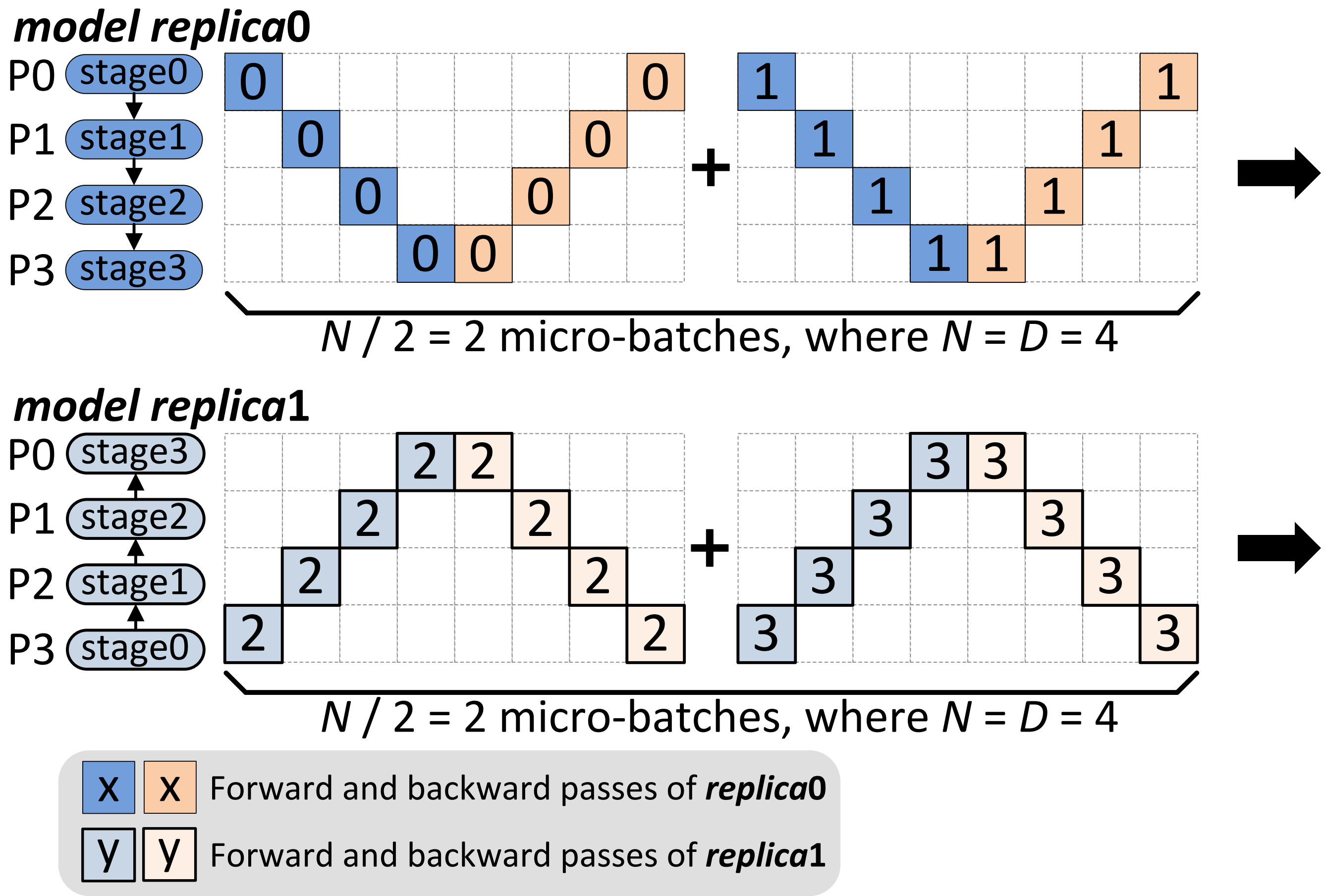
Schemes of pipeline parallelism

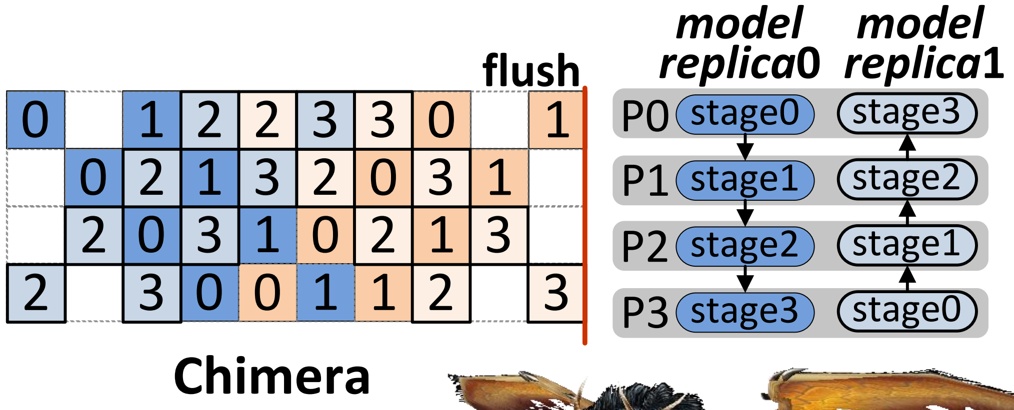


Bidirectional Pipelines



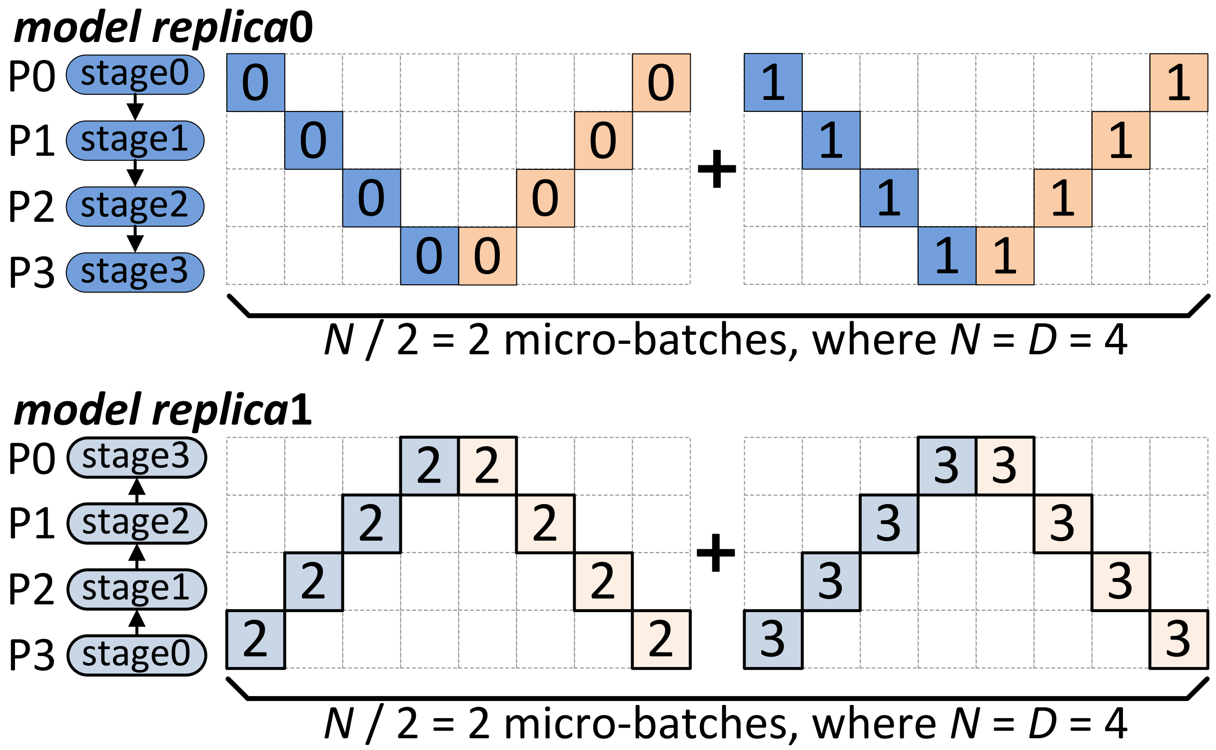
Bidirectional Pipelines

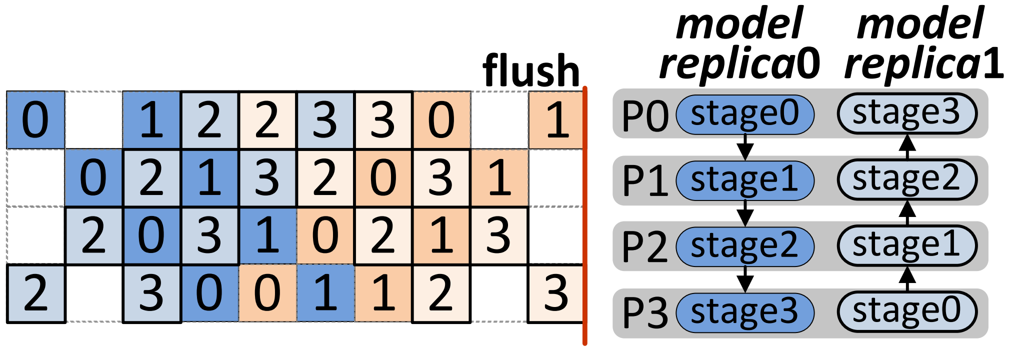




from Blizzard War3

Bidirectional Pipelines



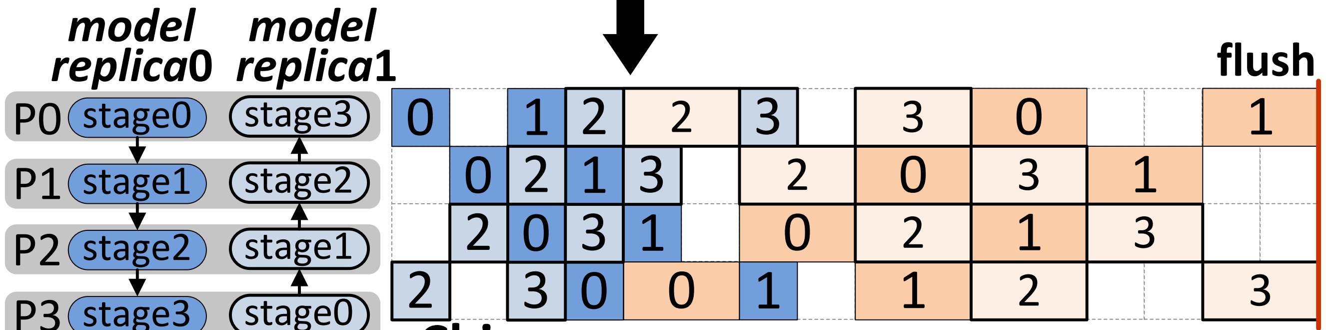


Chimera

from Blizzard War3

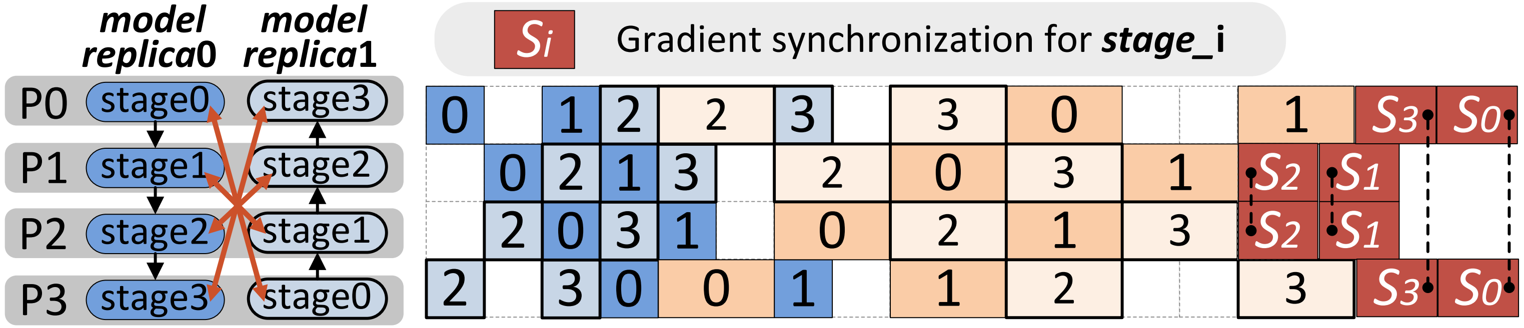
x x Forward and backward passes of ***replica*0**

y y Forward and backward passes of ***replica*1**



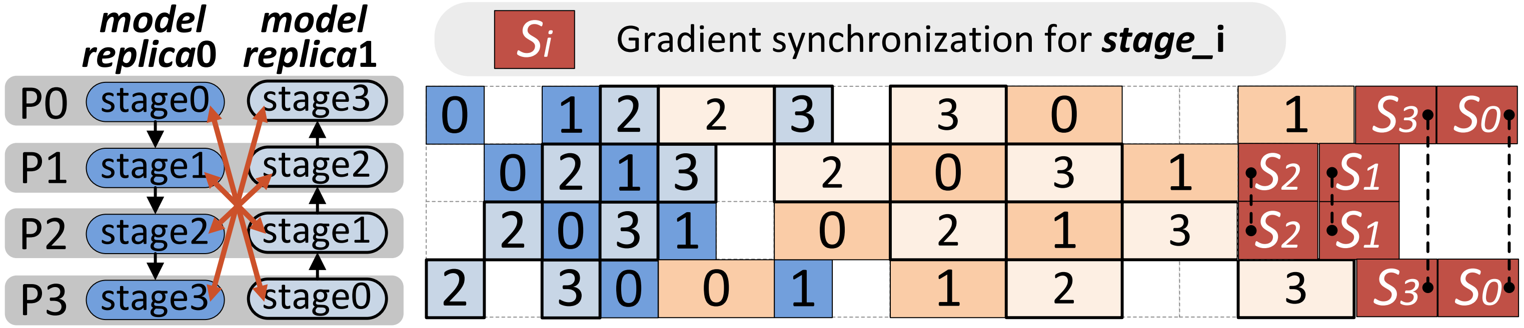
Chimera (backward is **2×** workload of forward)

Gradient synchronization between model replicas



(a) Gradient synchronization after all local computation is finished

Gradient synchronization between model replicas



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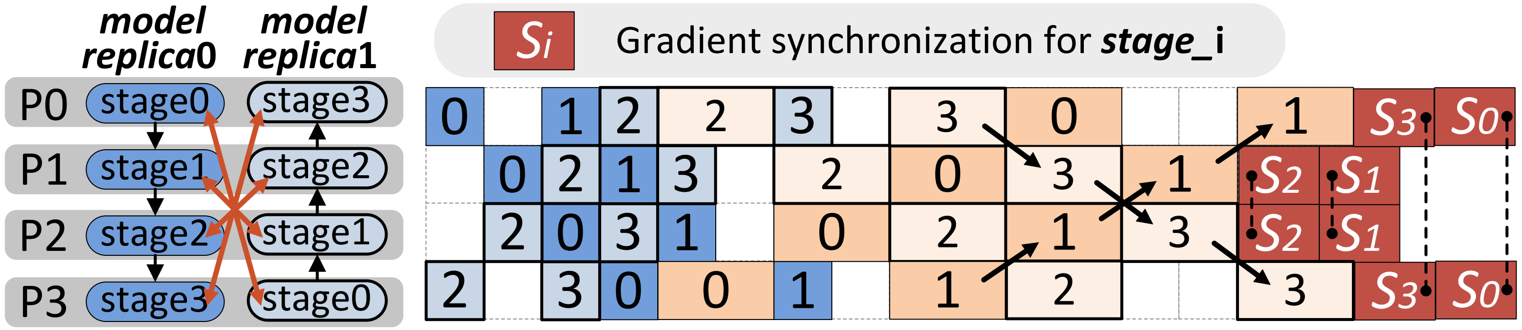
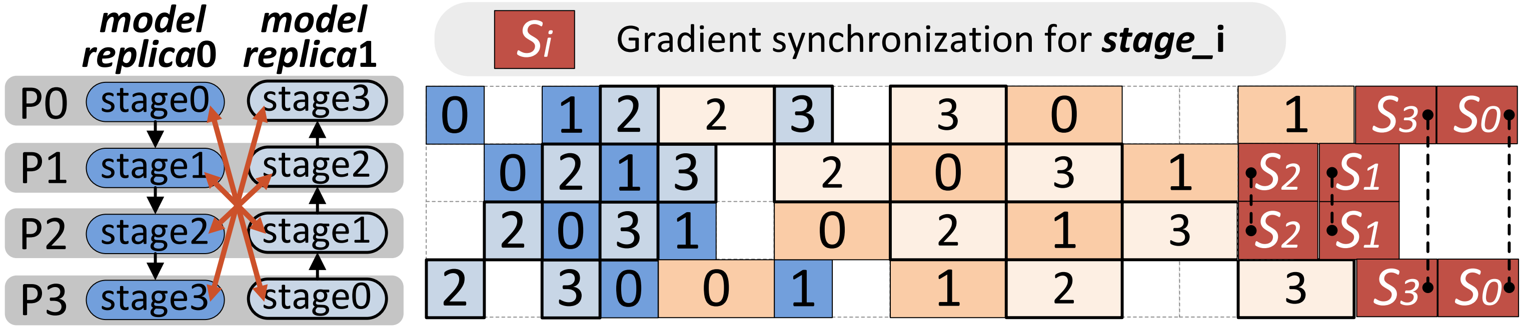


(b) Eager gradient synchronization for deeper overlapping

Gradient synchronization between model replicas



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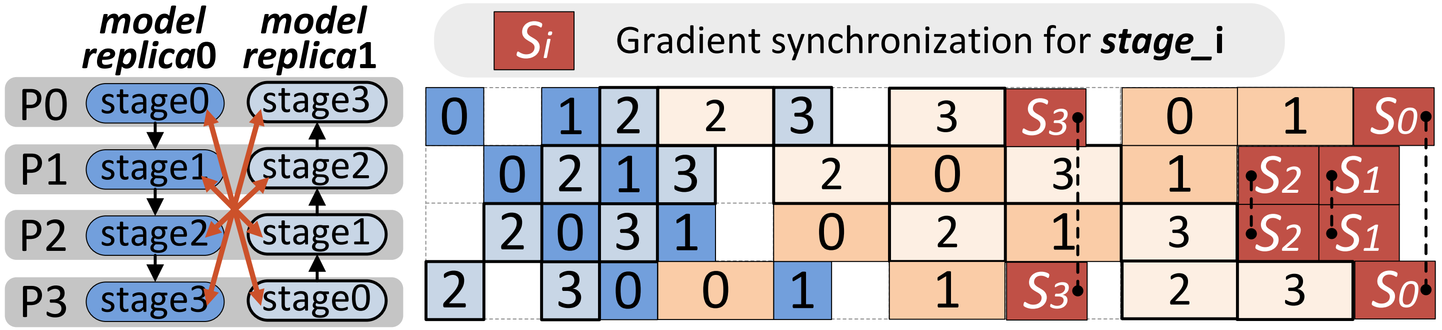
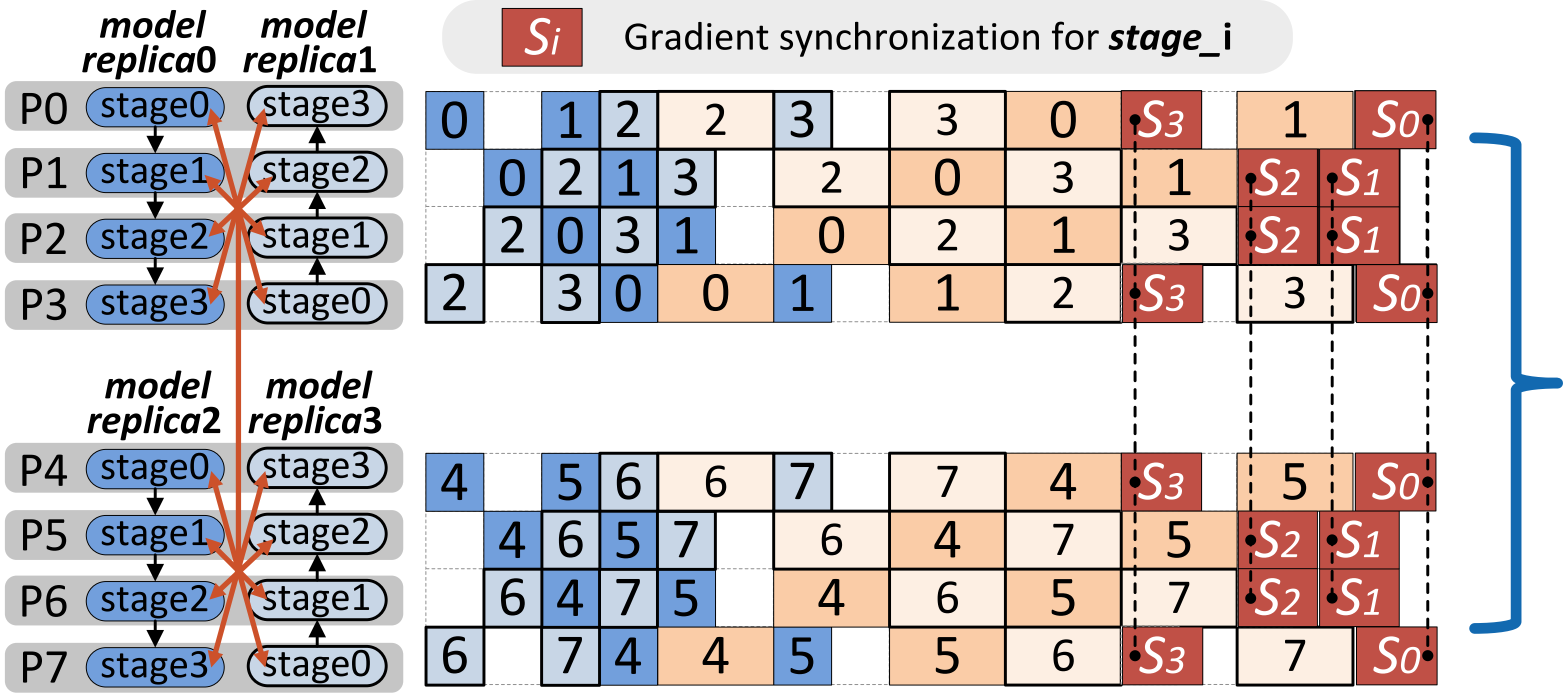


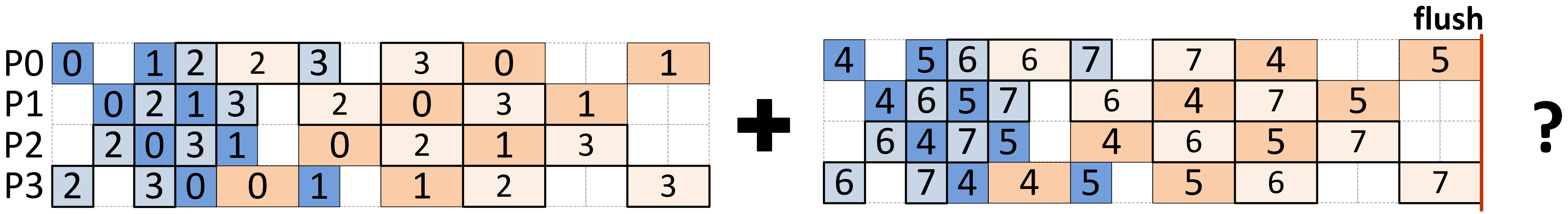
(b) Eager gradient synchronization for deeper overlapping

Hybrid of pipeline and data parallelism



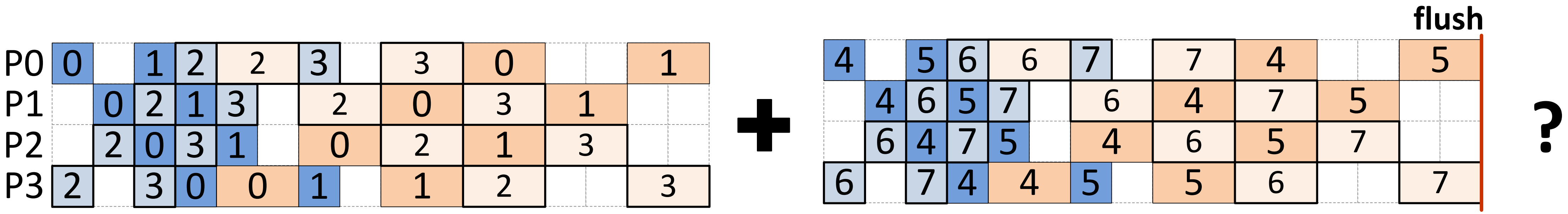
2x pipelines, i.e., ***W*** (width) **= 2**

Scale to more micro-batches



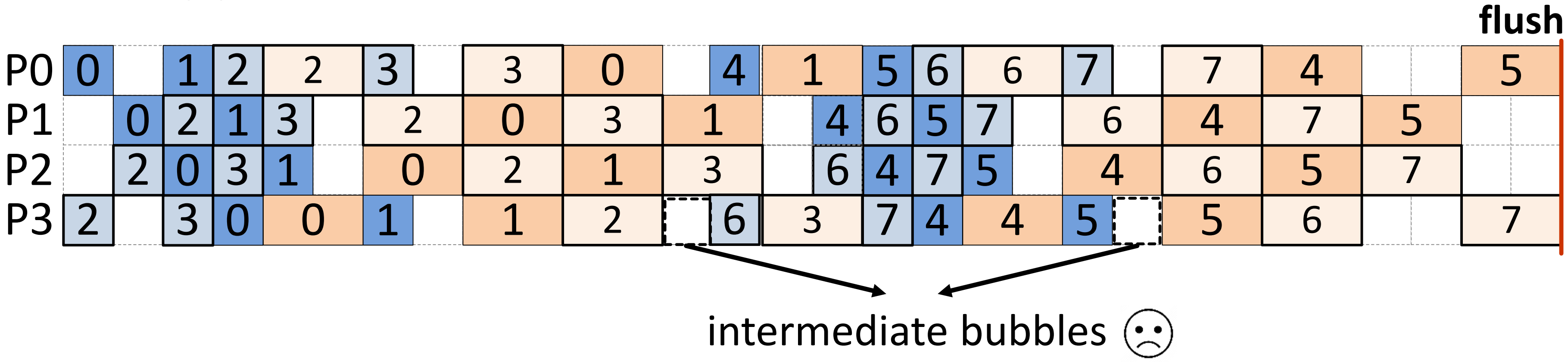
N=2***D*** micro-batches, where ***D***=4

Scale to more micro-batches



***N*=2*D* micro-batches, where *D*=4**

Method (1): Direct concatenation



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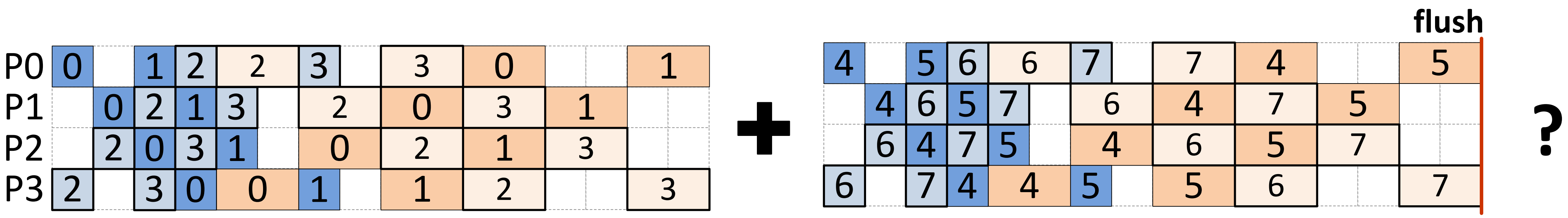
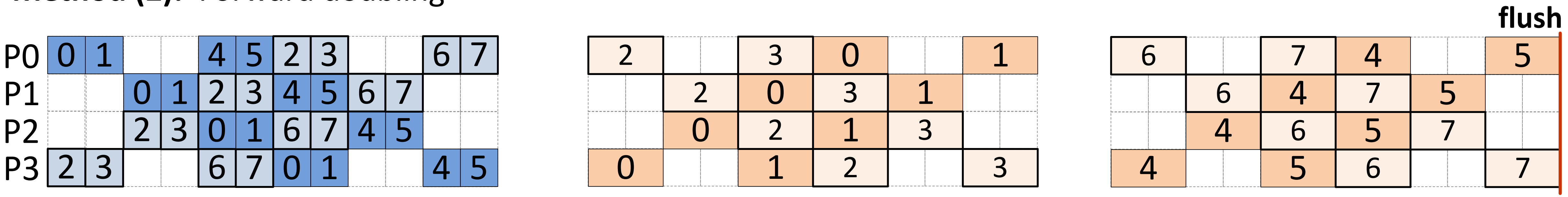


N=2***D*** micro-batches, where ***D***=4

Method (2): Forward doubling



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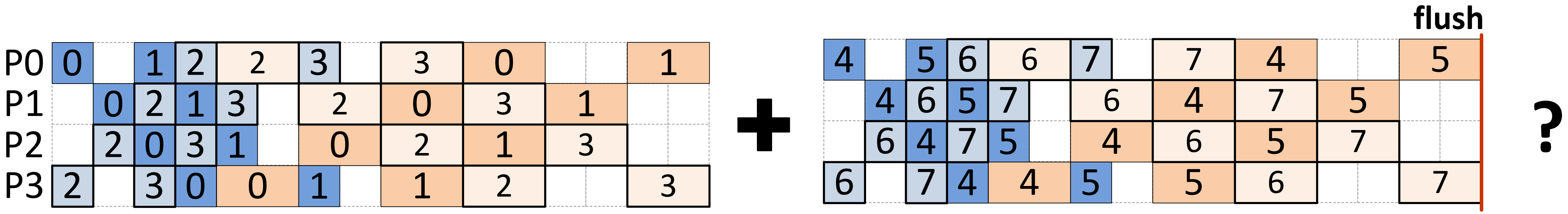

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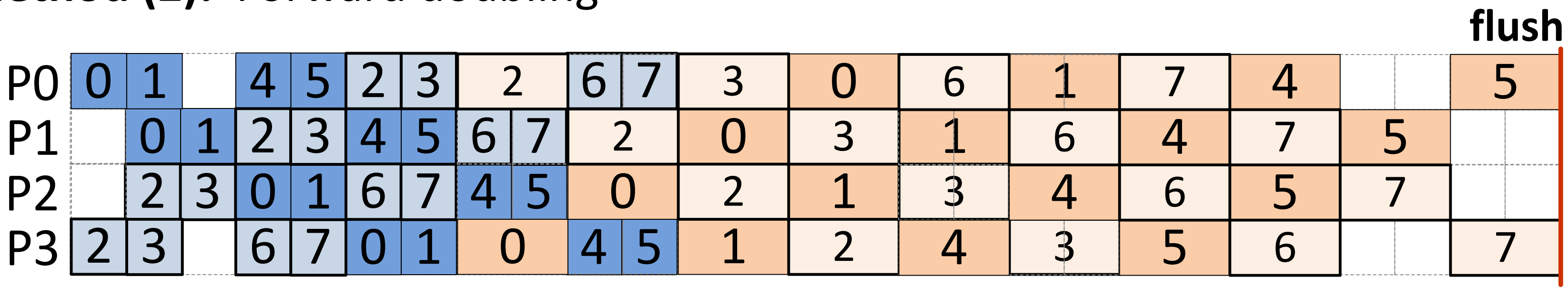
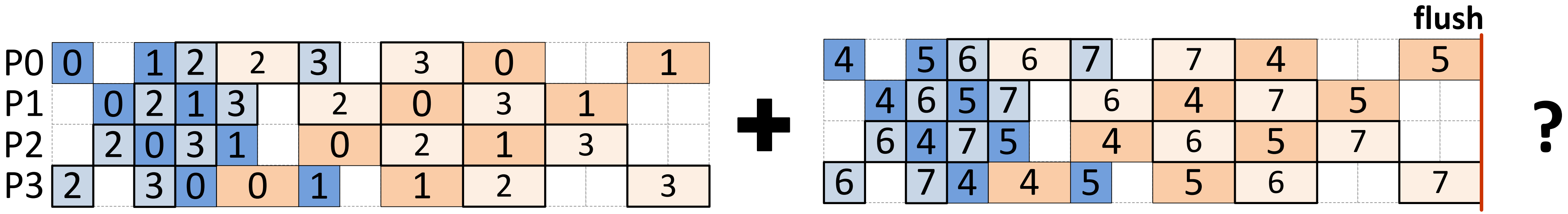


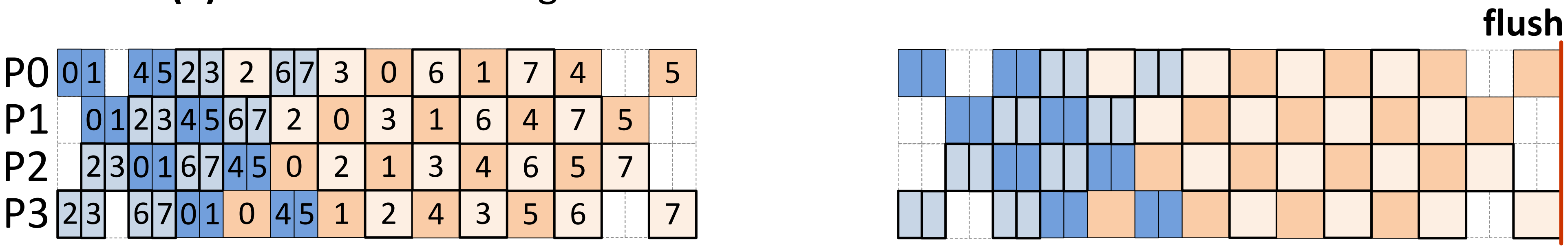
- **eliminate intermediate bubbles**
- **2x activation memory**

Scale to more micro-batches



N=2***D*** micro-batches, where ***D***=4

Method (3): Backward halving



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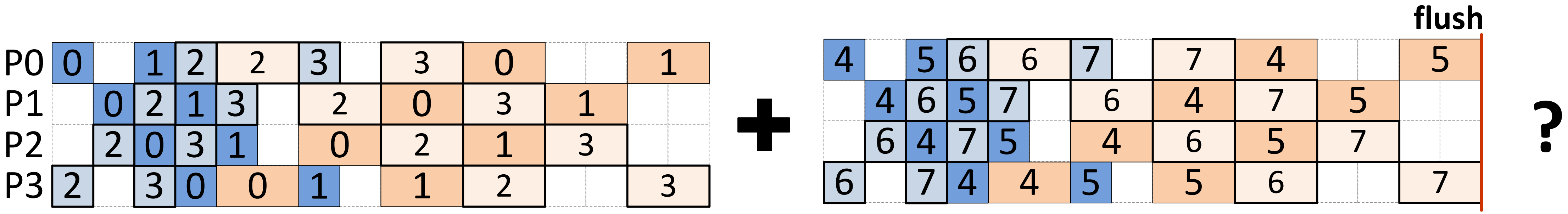

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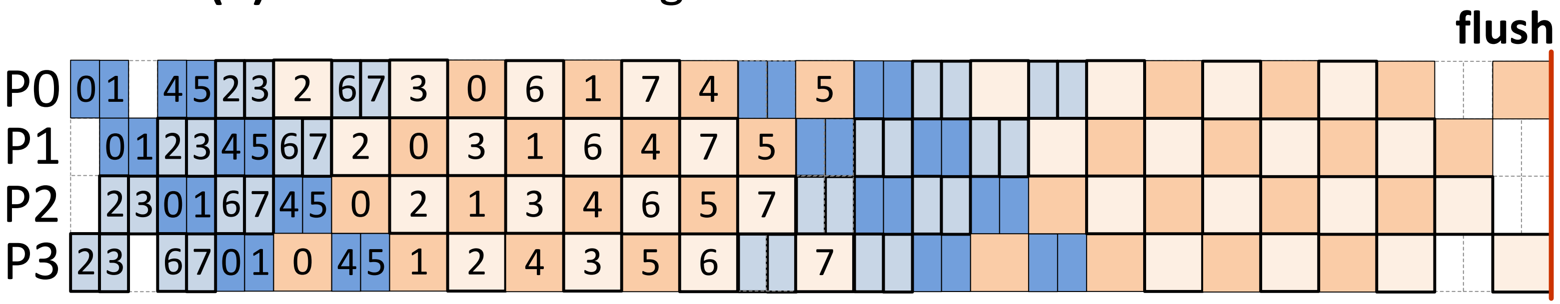
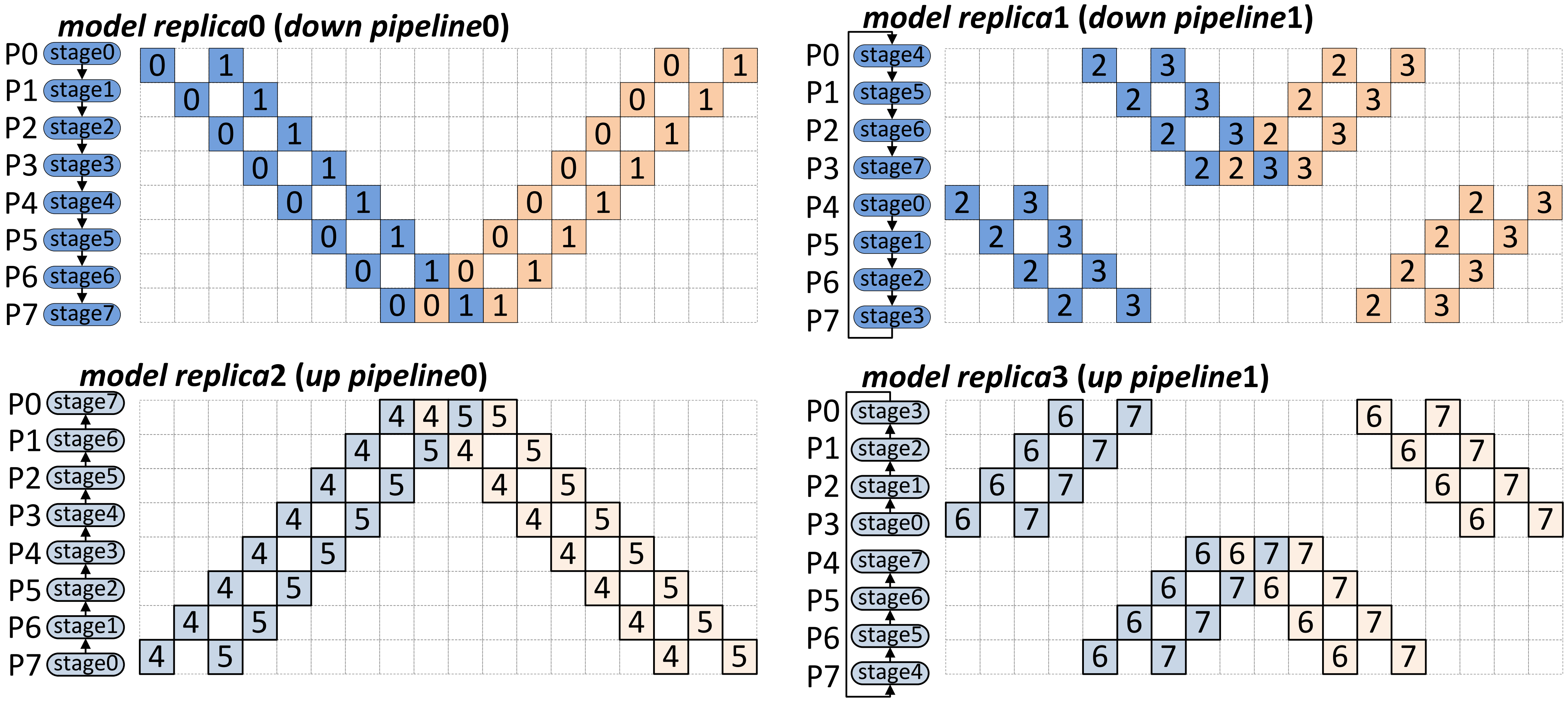


- eliminate intermediate bubbles
- **halving micro-batch size**

Generalize to more pipelines



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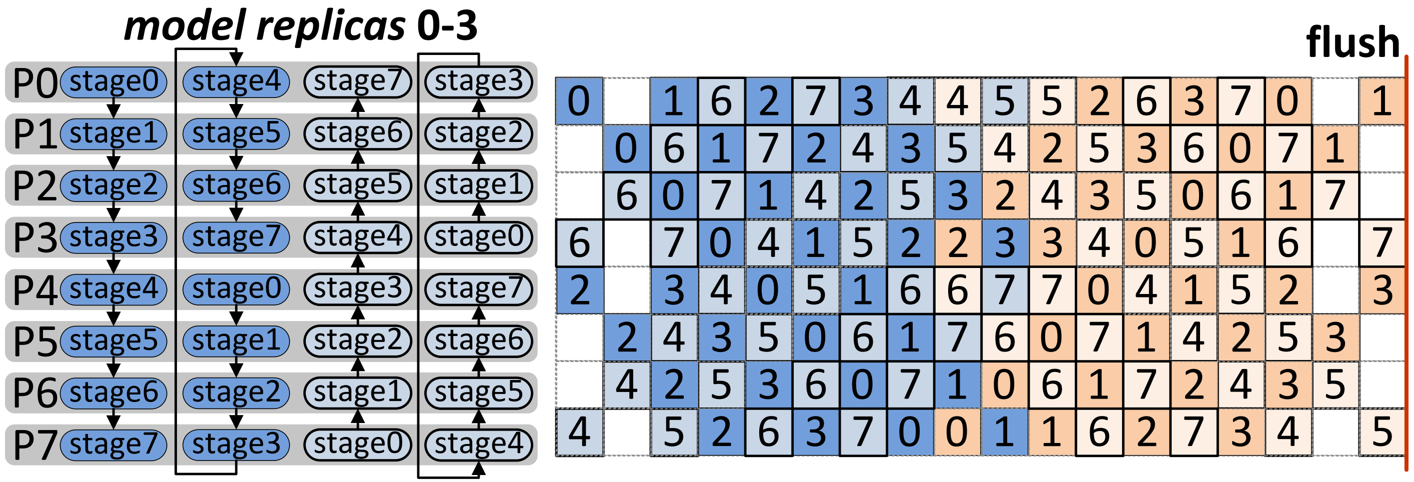
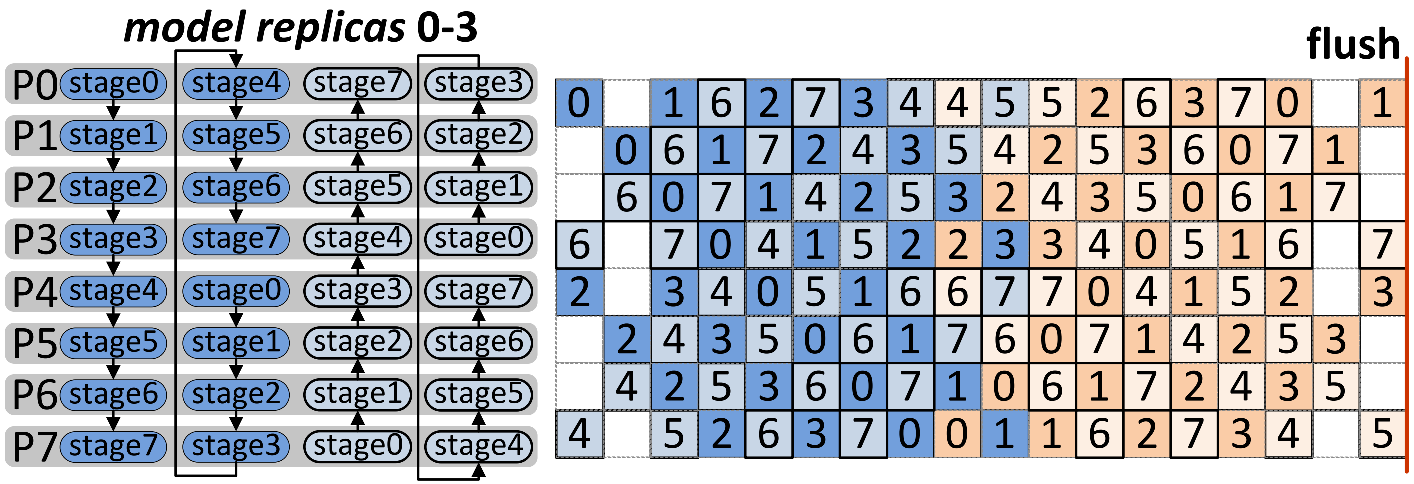


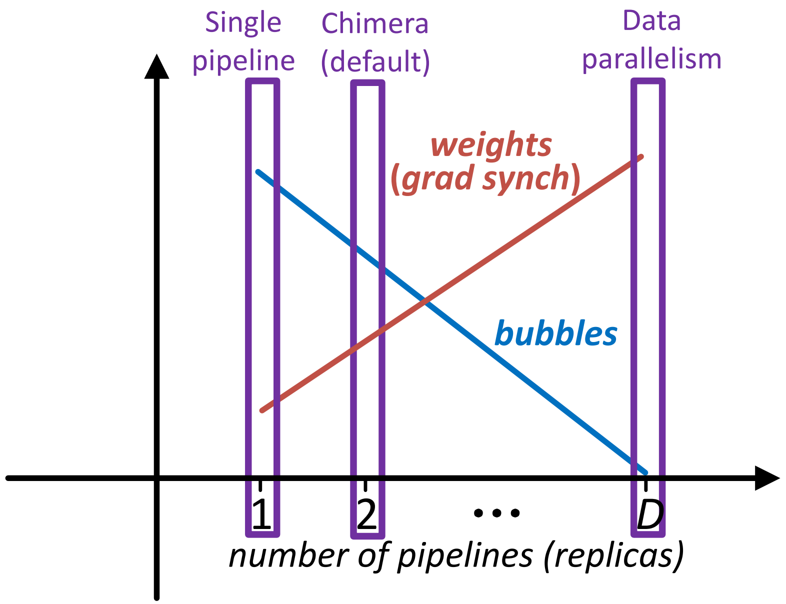
Chimera (a combination of four pipelines)

Generalize to more pipelines



Chimera (a combination of four pipelines)

Chimera with ***r*** pipelines
(1 <= ***r*** <= ***D,*** if ***D*** is even)



Performance Modelling

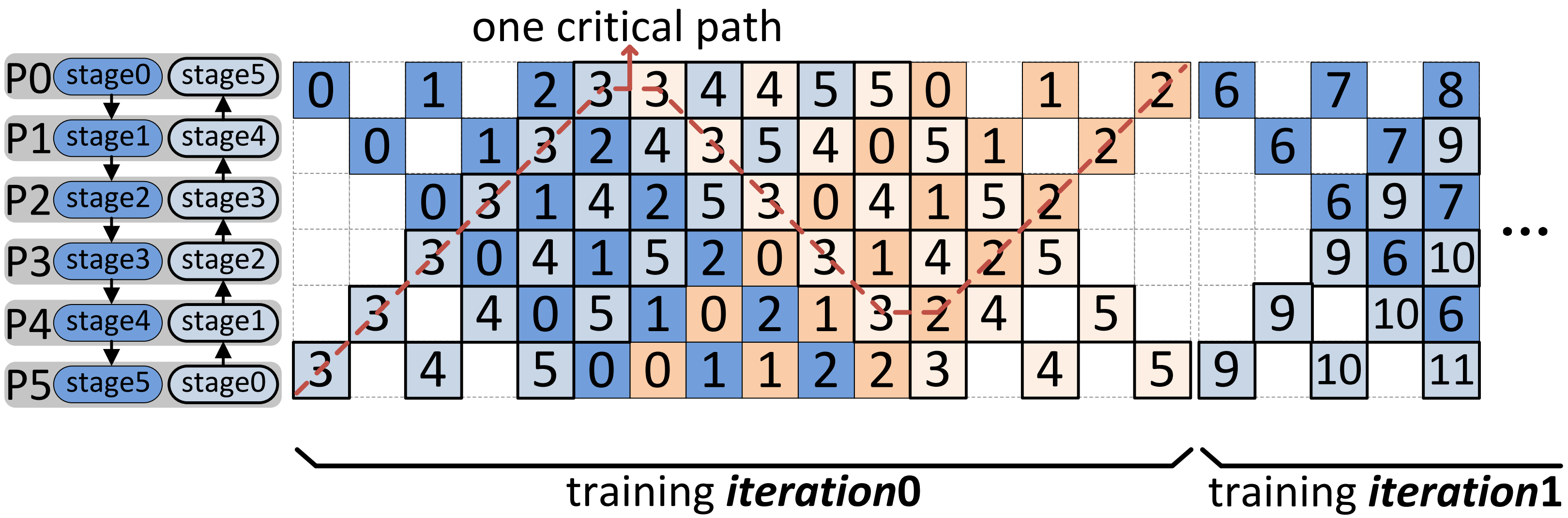
Given a *P*, how to decide the best *D* (*depth*) and *W* (*width*)?

C_f – the number of forward passes in critical path

C_b – the number of backward passes in critical path

$C_f = 6$

$C_b = 10$



The runtime of a single training iteration is

$$T = (F_t + Comm_{p2p})C_f + (B_t + Comm_{p2p})C_b +$$

Performance Modelling

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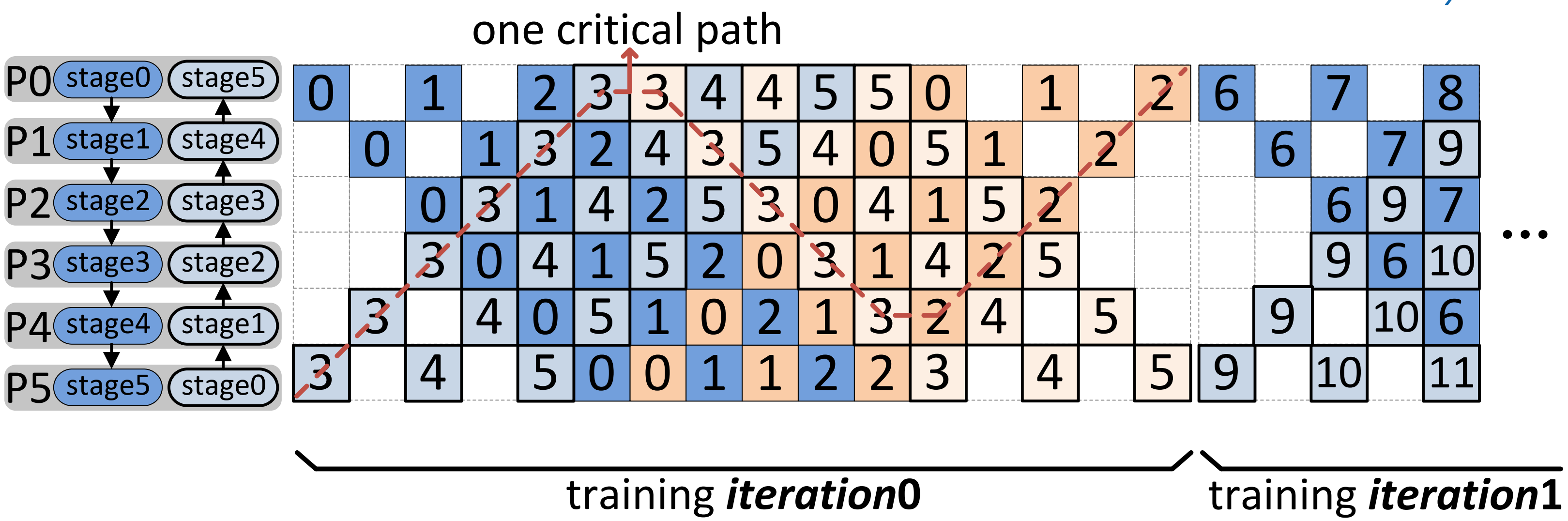
Rabenseifner's algorithm for allreduce:

$$Comm_{allreduce} = 2(log_2 r)\underbrace{\alpha}_{latency} + 2(r-1)\underbrace{\beta}_{bandwidth} L/r$$



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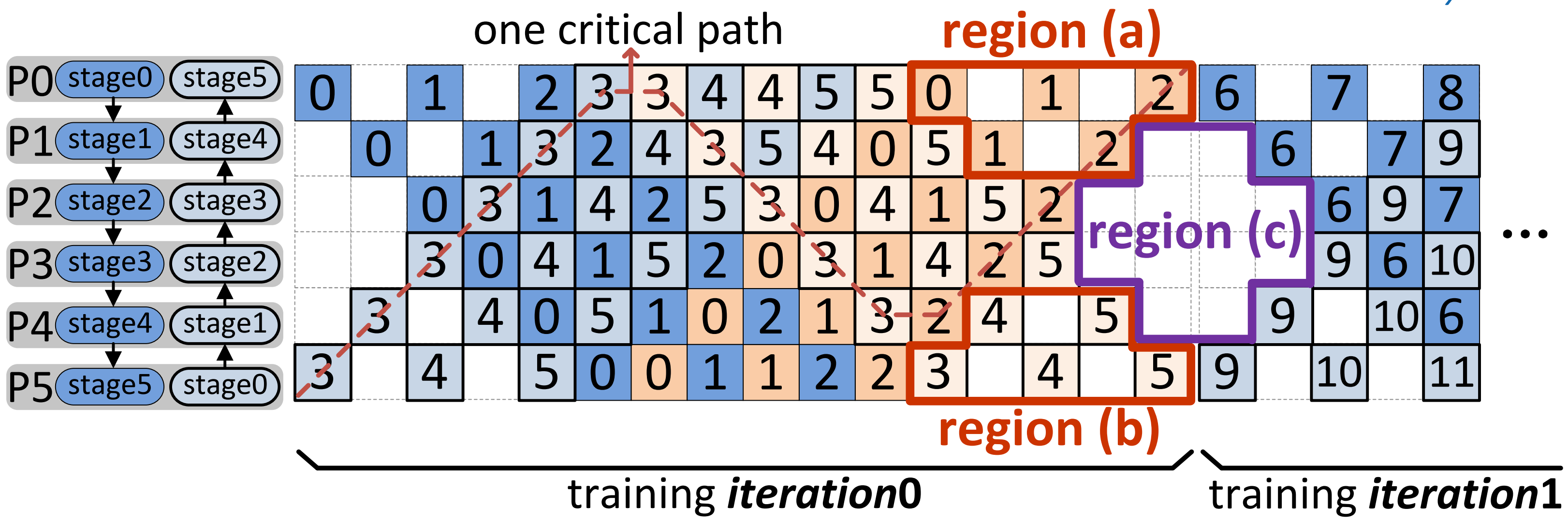


The runtime of a single training iteration is

$$T = (F_t + Comm_{p2p})C_f + (B_t + Comm_{p2p})C_b + max\{Comm_{unoverlapped}(i) : i \in [0, D-1]\}.$$

Evaluation

- **CSCS Piz Daint** supercomputer
  - Each node contains a 12-core Intel Xeon E5-2690 CPU, and one NVIDIA Tesla P100 GPU
  - Cray Aries interconnected network
- A small cluster with 32 NVIDIA Tesla V100 GPUs
  - 4x8 GPUs connected by NVLink and Infiniband
- Baselines include all schemes listed in Table 1: **GPipe**, **GEMS**, **DAPPLE**, **PipeDream**, **PipeDream-2BW**
- All schemes are implemented in **PyTorch** with **GLOO** distributed backend for both ***P2P*** and ***allreduce***

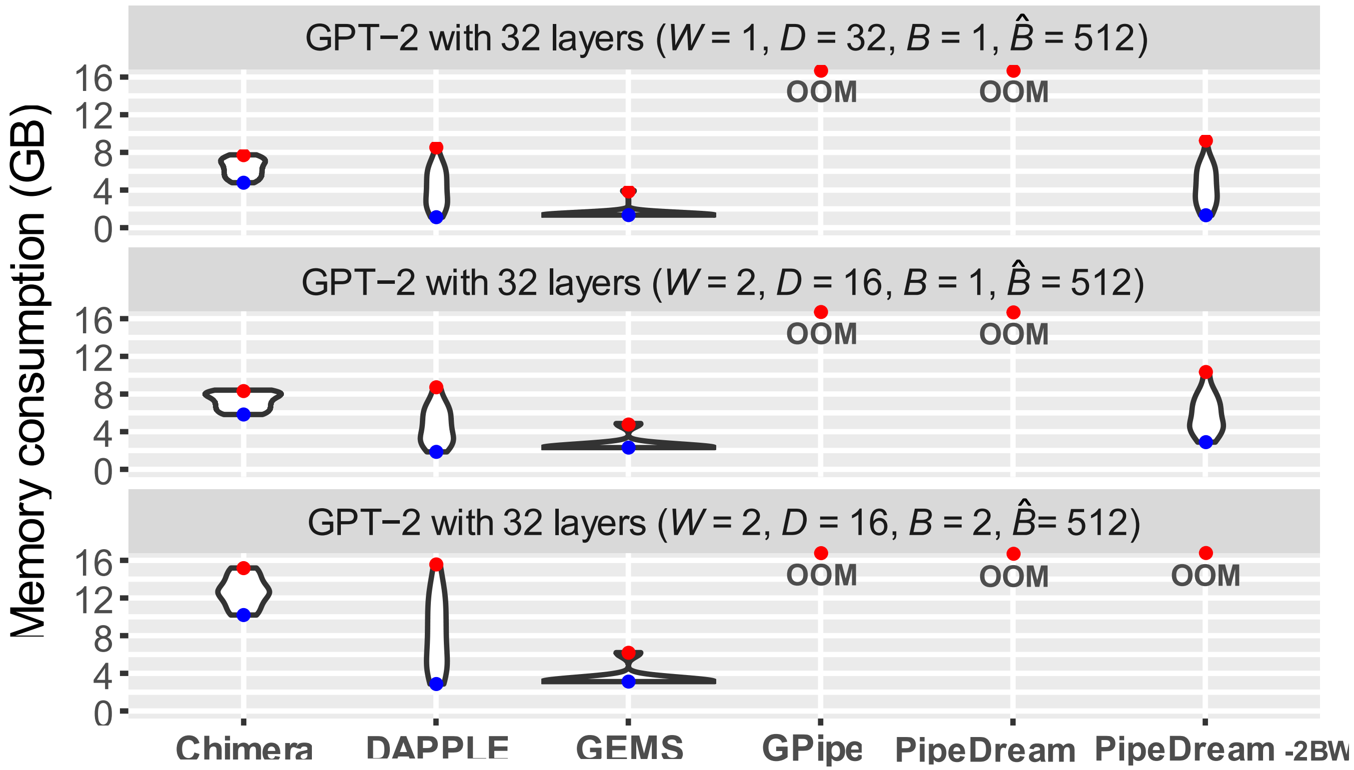
Table 3. Neural networks used for evaluation

Networks	Layers	Parameters	Mini-batch size
Bert-48	48	669,790,012	>=256
GPT-2	64	1,389,327,360	>=512

Table 4. List of symbols

D	The number of pipeline stages (*depth*)
W	The number of replicated pipelines (*width*) for data parallelism
B	Micro-batch size
$\hat{B}$	Mini-batch size ($= B * N * W$)
R	Activation recomputation is required

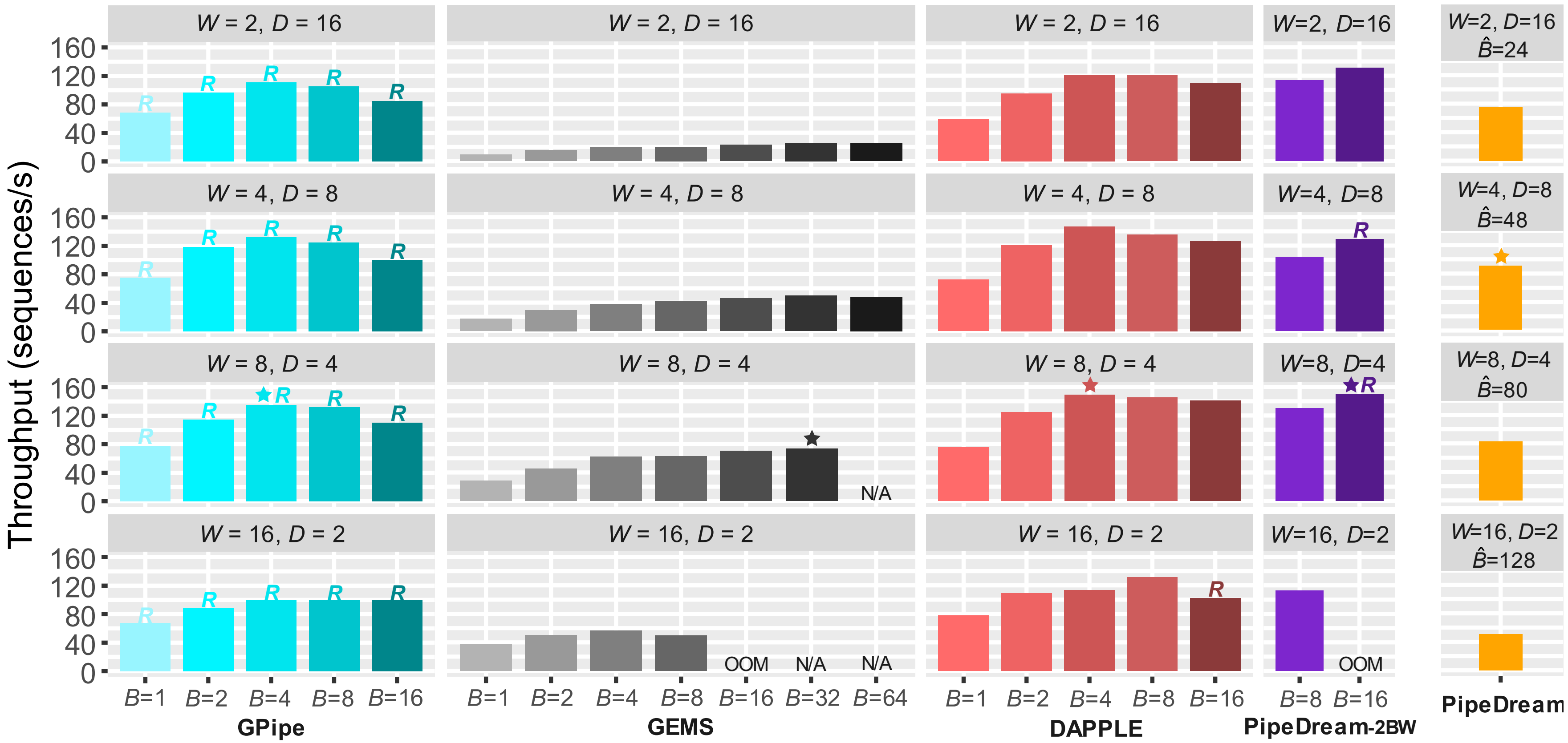
Memory consumption



Pipeline Schemes	Weights Memory	Activations Memory
PipeDream [38]	$[M_\theta,\ D*M_\theta]$ [1] 👎	$[M_a,\ D*M_a]$ [1] 👍
PipeDream-2BW [39]	$2M_\theta$ 👍	$[M_a,\ D*M_a]$ [1] 👍
GPipe [26]	M_θ 👍	$N*M_a$ 👎👎
GEMS [28]	$2M_\theta$ 👍	M_a 👍👍
DAPPLE [16]	M_θ 👍	$[M_a,\ D*M_a]$ [1] 👍
Chimera (this work)	$2M_\theta$ 👍	$[(D/2+1)M_a, D*M_a]$ [1] 👍+

Tuning for baselines

The parameters of ***D***, ***W***, and ***B*** affect the performance significantly.

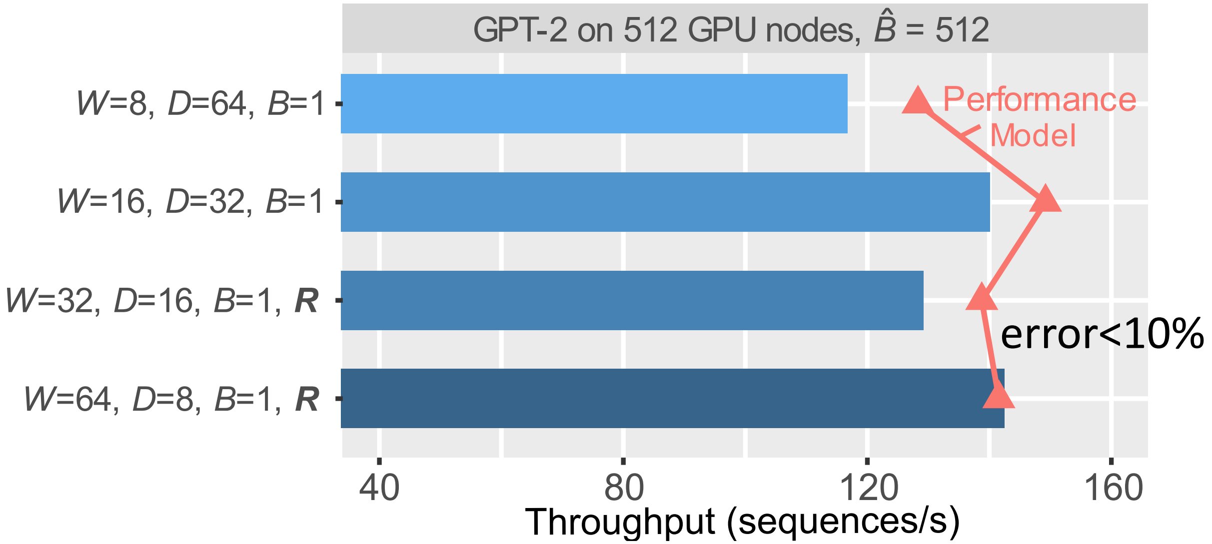


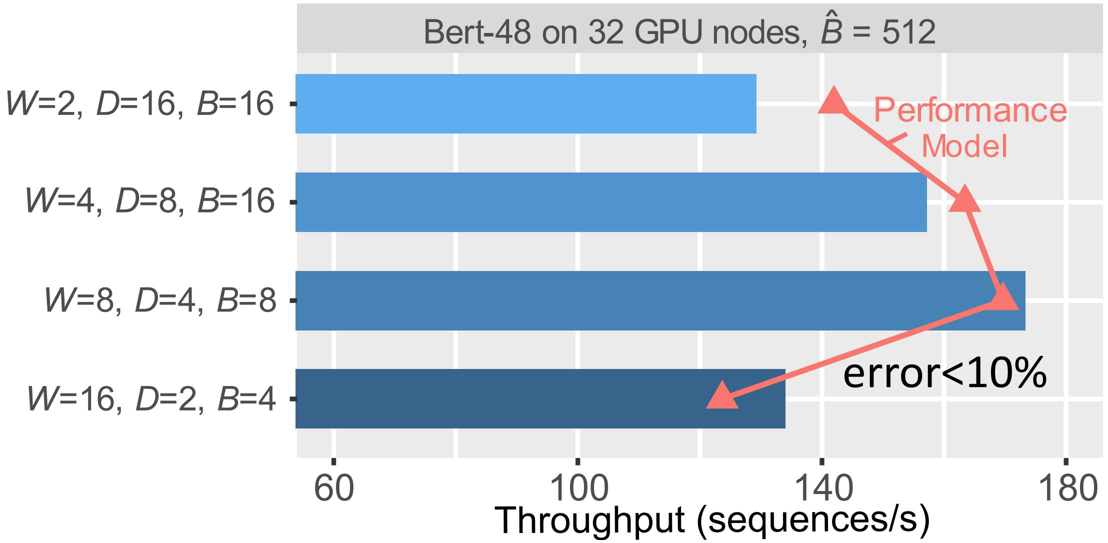
Performance tuning for the baselines for Bert-48 on 32 GPU nodes.
R denotes **activation recomputation** to avoid **OOM**. $Star$ marks the best performance.

Performance modelling of Chimera

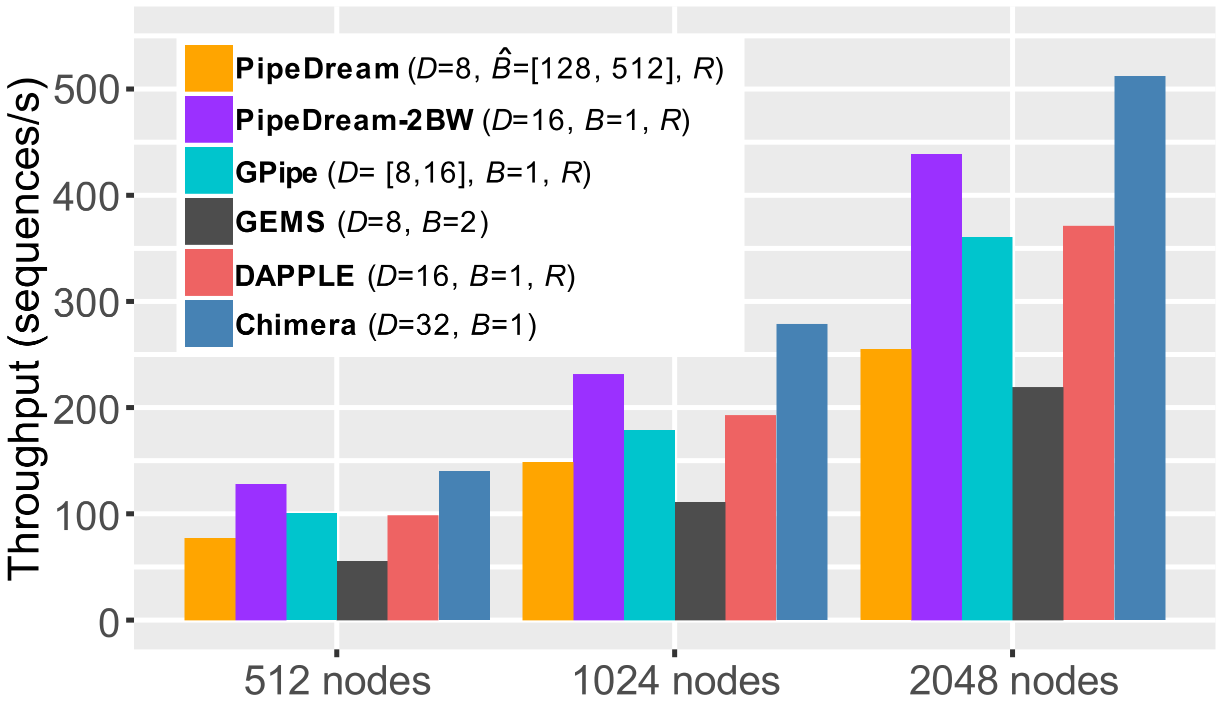
The runtime of a single training iteration is modelled as

$$T = (F_t + Comm_{p2p})C_f + (B_t + Comm_{p2p})C_b + max\{Comm_{unoverlapped}(i) : i \in [0, D-1]\}.$$





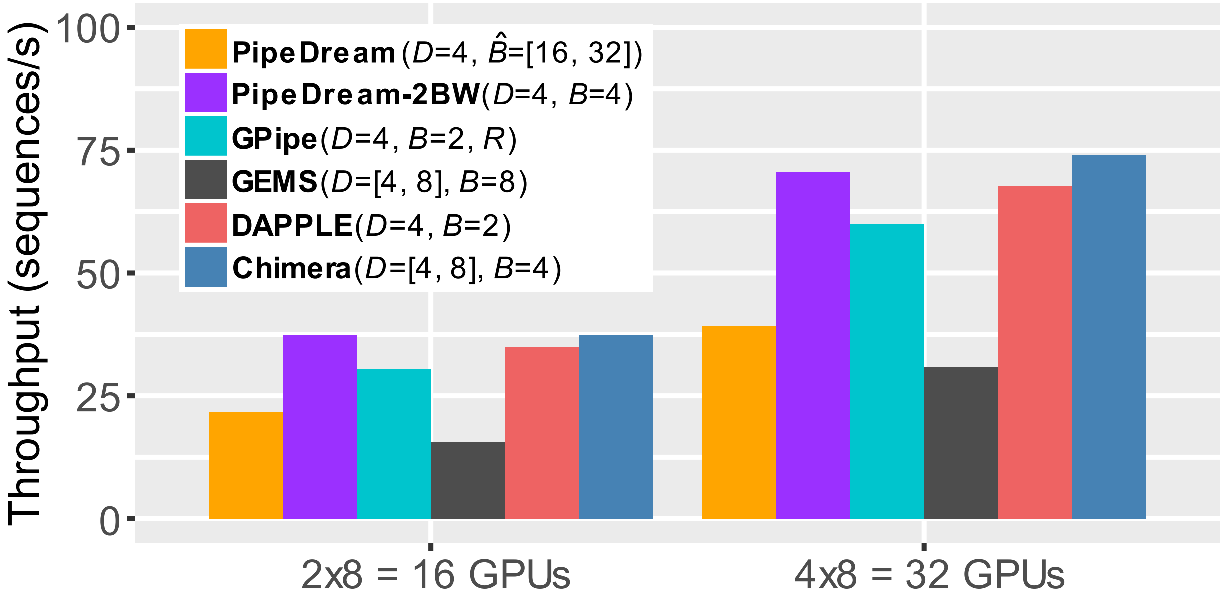
Weak scaling



Weak scaling for GPT-2 on Piz Daint
(512 to 2048 GPU nodes)

- **1.38x - 2.34x speedup over synchronous approaches (GPipe, GEMS, DAPPLE)**
  - Less bubbles
  - More balanced memory thus no recomputation
- **1.16x - 2.01x speedup over asynchronous approaches (PipeDream-2BW, PipeDream)**
  - More balanced memory thus no recomputation
  - Gradient accumulation thus low synch frequency

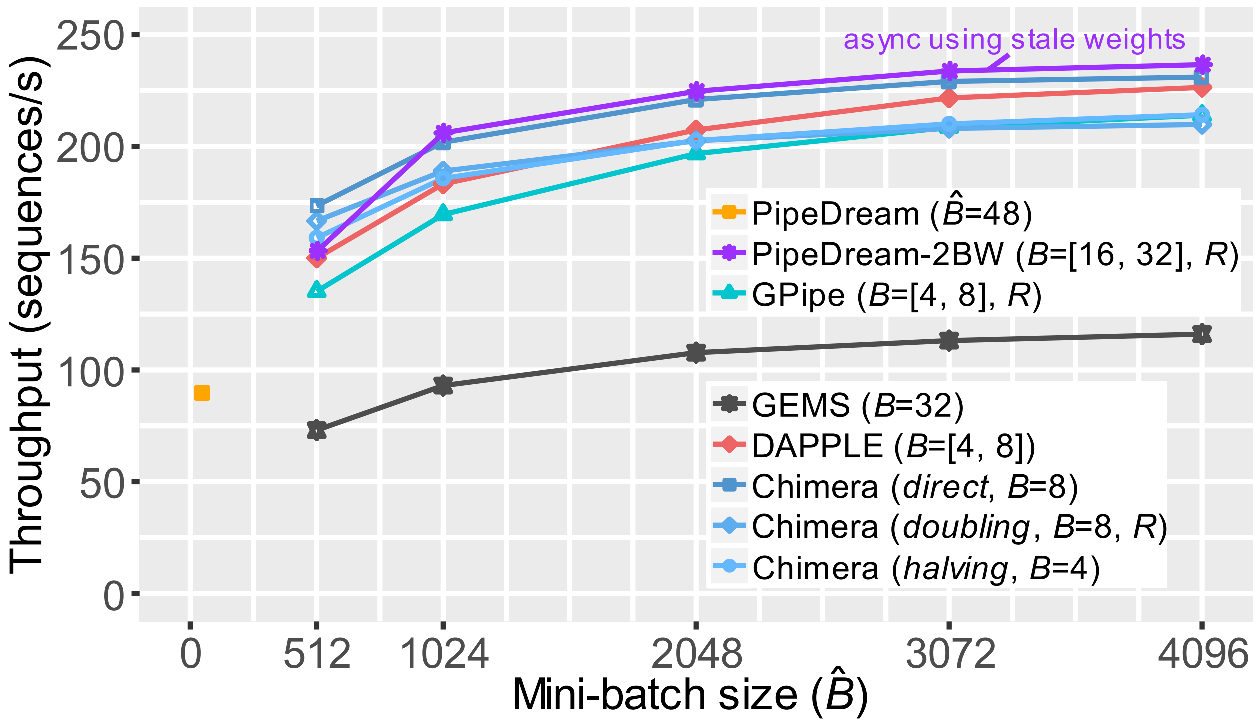
Weak scaling



Weak scaling for Bert-48 on a cluster with 32 V100 GPUs, sequence length is 512.

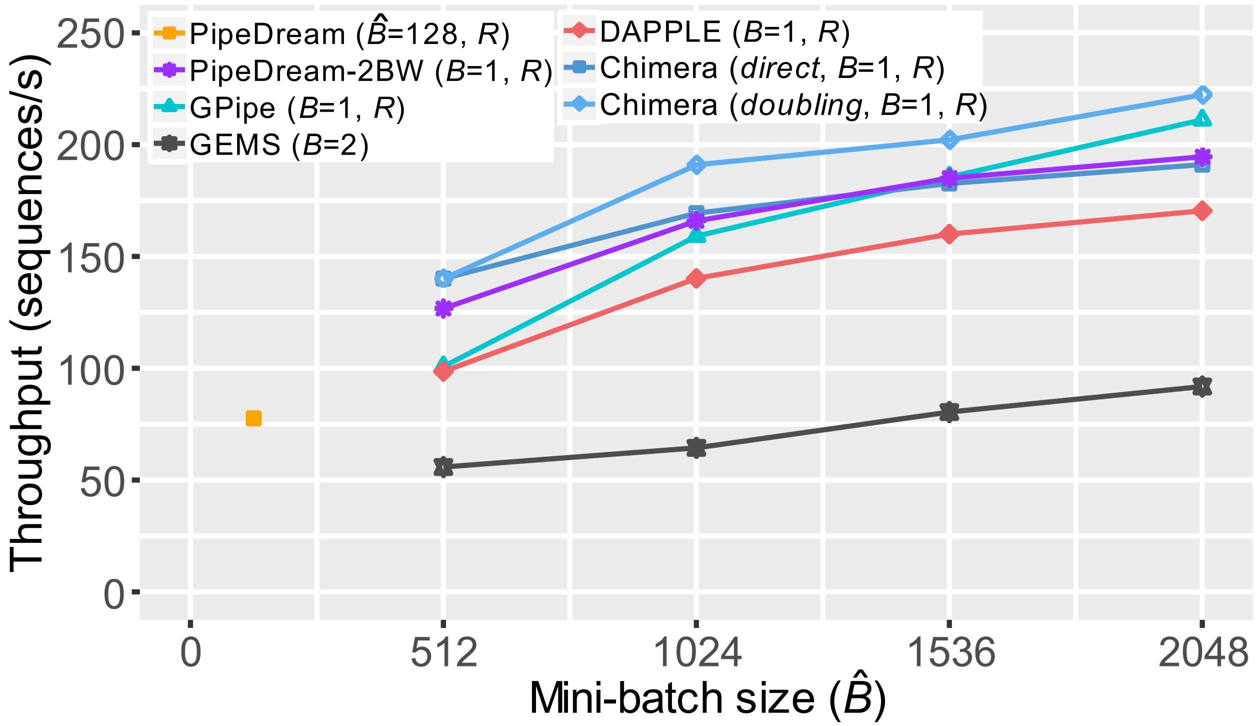
- **Similar conclusion holds for BERT on the cluster with newer GPUs and heterogeneous interconnected networks.**

Scale to large mini-batches

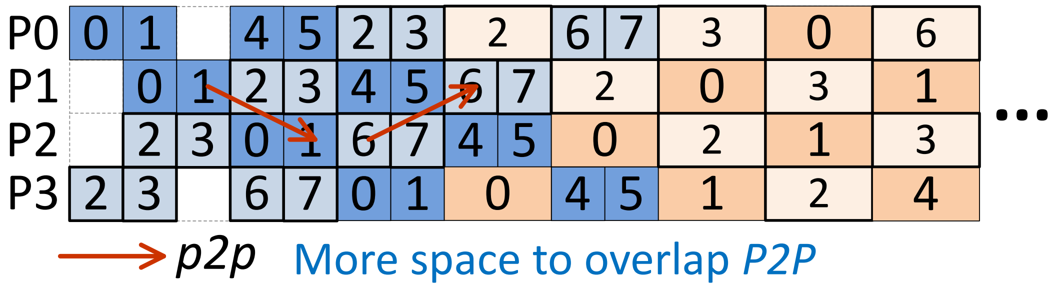


Scale to large mini-batch size for Bert-48
on 32 GPU nodes of Piz Daint.

Scale to large mini-batches

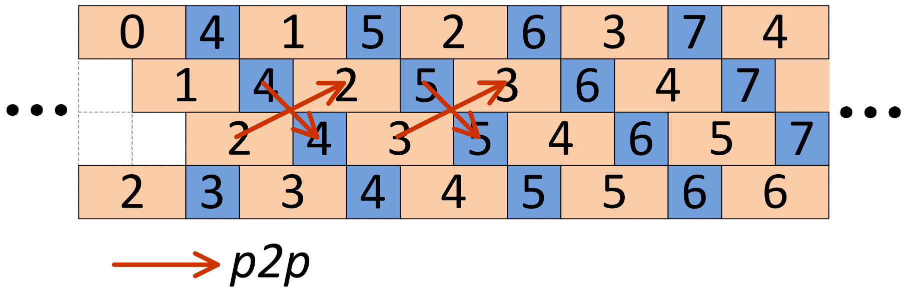


Scale to large mini-batch size for GPT-2 on
512 GPU nodes of Piz Daint.



More space to overlap *P2P*

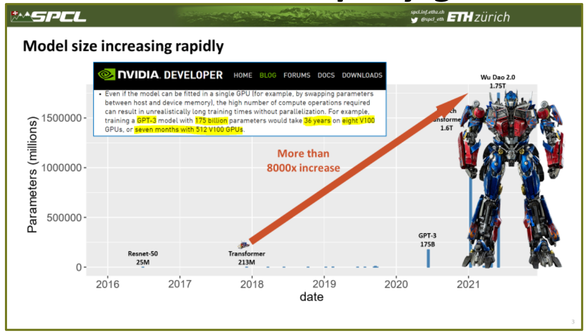
Chimera with *forward doubling*



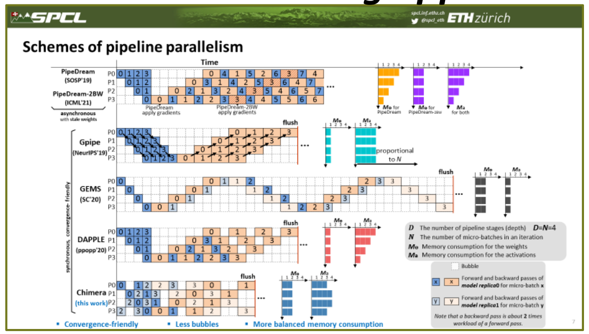
PipeDream-2BW

Conclusion

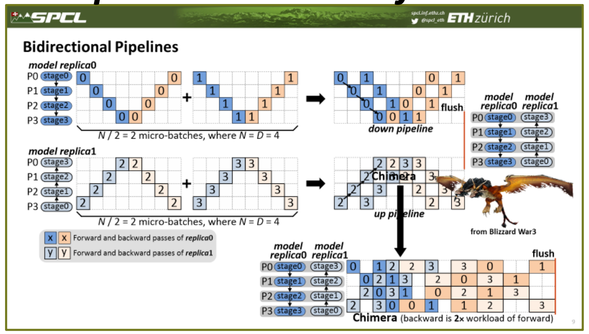
1. Model size rapidly grows



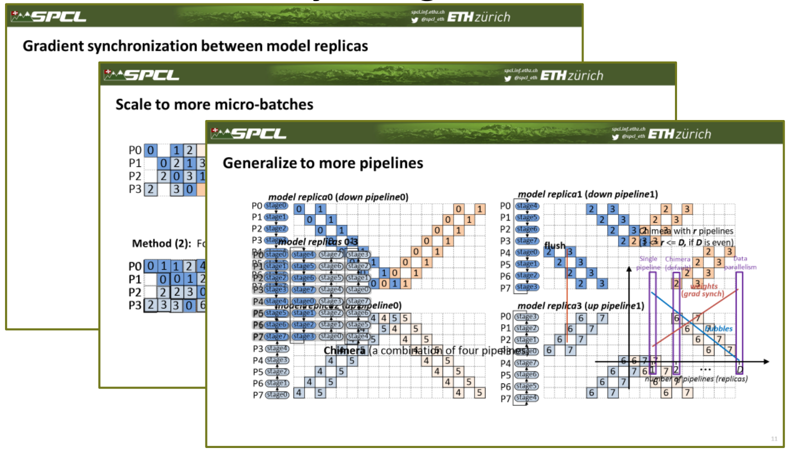
2. Distributed training approaches



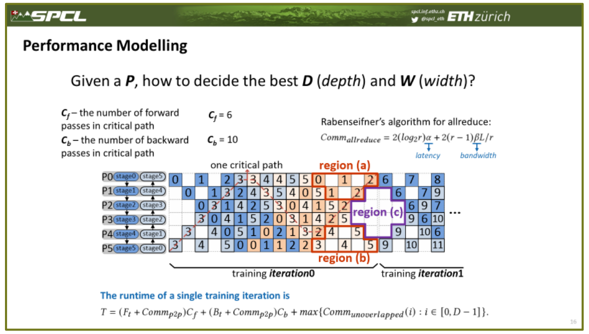
3. Pipeline schedule of Chimera



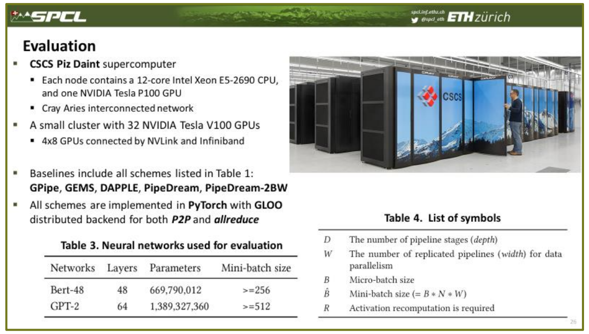
4. Scalability and generalization



5. Performance modelling



6. Evaluation on supercomputer



For any questions contact: ***shigangli.cs@gmail.com***

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