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2nd High Performance Machine Learning Workshop - HPML

Theoretical Scalability Analysis of Distributed Deep Convolutional Neural Networks

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Why Deep Learning now?

- Explosion in the amount of data available today
  - *Reliable training of the DNNs*
- Increased computing capabilities of current hardware
  - *Enables training in reasonable time*
- Significant algorithmic advances +
  development of open source frameworks for DNNs
  - *Facilitate the research and use of DNNs*
  - *Broaden the domains to which DNNs are being applied*

Deep Learning Applications

Key (and growing number of) applications:

- Text recognition and language translation,
- Image classification,
- Adaptive user profile,
- Voice recognition systems,
- Autonomous driving,
- Weather forecast, etc.

→ In general, social networks and big data analytics

Distributed training on HPC clusters

- Inference can be performed on low-end devices, but…
- training requires advanced HPC solutions
- So, what is important to achieve good performance?
  - Processor performance
  - Memory bandwidth
  - Network interconnect bandwidth
  - Number of cluster nodes
  - Parallelism model
  - Algorithm parameters

Modeling the performance
of CNNs Distributed Training

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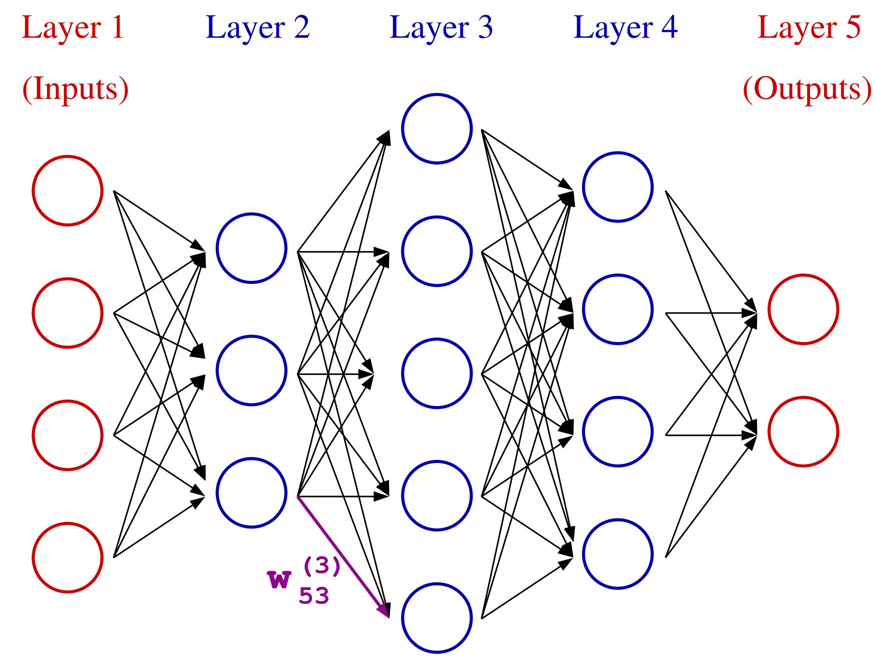
Training DNNs

Supervised training (GD)

Forward + Backward pass

Training 1 sample

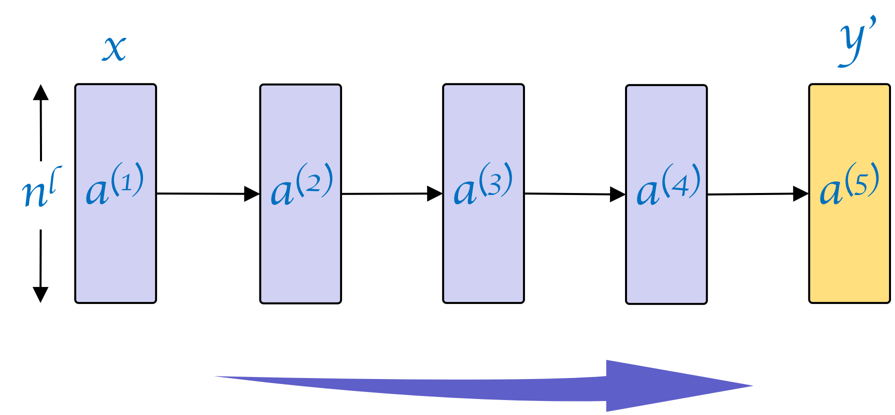
Assume given inputs x
and known outputs y



1. Forward pass (FP)

GEMV

$$\begin{aligned} a^{(1)} &= x, \\ a^{(l)} &= \sigma(z^{(l)}) = \sigma(W^{(l)}a^{(l-1)} + b^{(l)}) \in \mathbb{R}^{n_l}, \\ &\quad l = 2, 3, \ldots, L, \\ \tilde{y} &= a^{(L)}. \end{aligned}$$



Training DNNs

2. Backward pass (BP)

2.1. Gradient computation (GC)

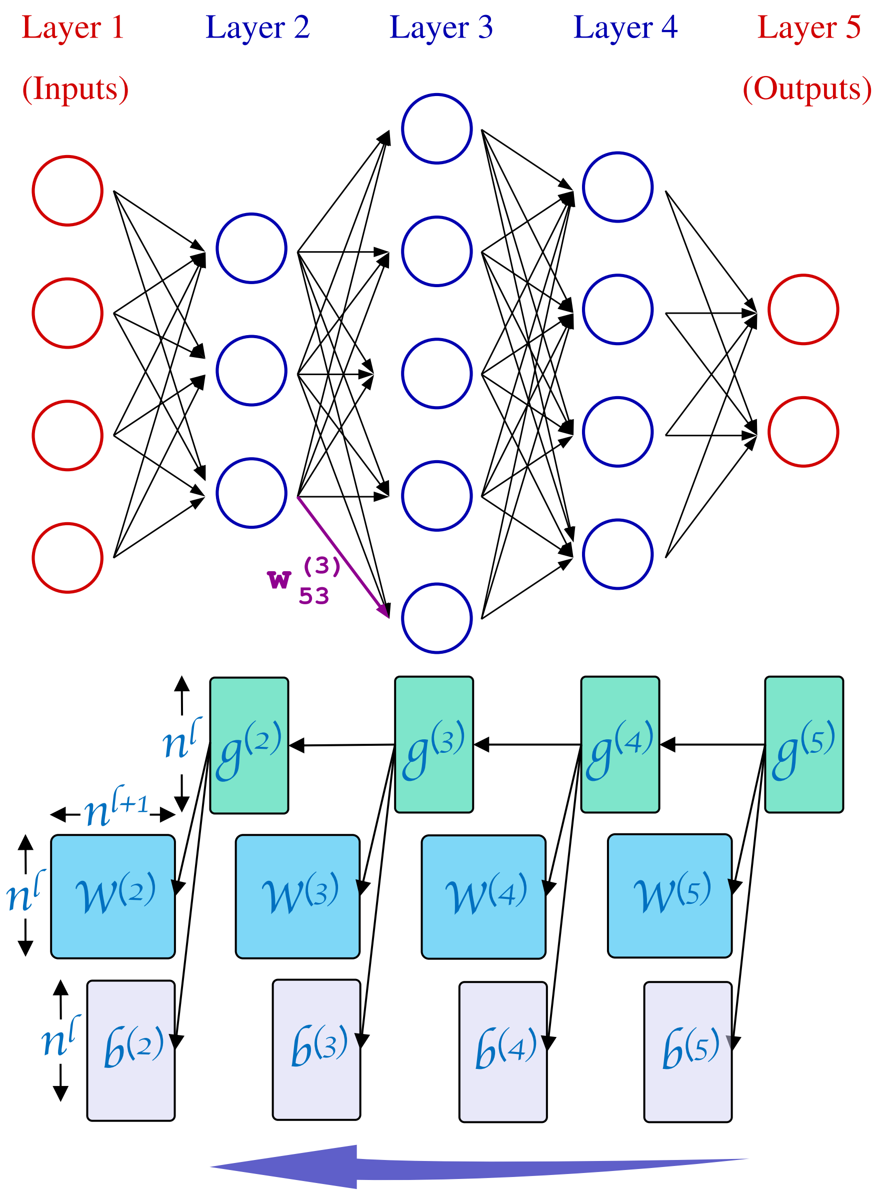
GEMV

$$
\begin{aligned}
g^{(L)} &= D^{(L)}(a^{(L)} - \tilde{y}), \\
g^{(l)} &= D^{(l)}(W^{(l+1)})^T g^{(l+1)}, \\
&\qquad l = L-1, L-2, \ldots, 2;
\end{aligned}
$$

2.2. Weight update (WU)

Outer-product

$$
\begin{aligned}
W^{(l)} &= W^{(l)} - \eta\, g^{(l)} (a^{(l-1)})^T, \\
b^{(l)} &= b^{(l)} - \eta\, g^{(l)}, \qquad l = L, L-1, \ldots, 2.
\end{aligned}
$$



High-performance Batched Training

From a single sample to a batch of b samples (SGD):

1. **Forward pass (FC)**

$$Z^{(l)} = W^{(l)} A^{(l-1)} + B^{(l)}$$ GEMM

2. **Backward pass**

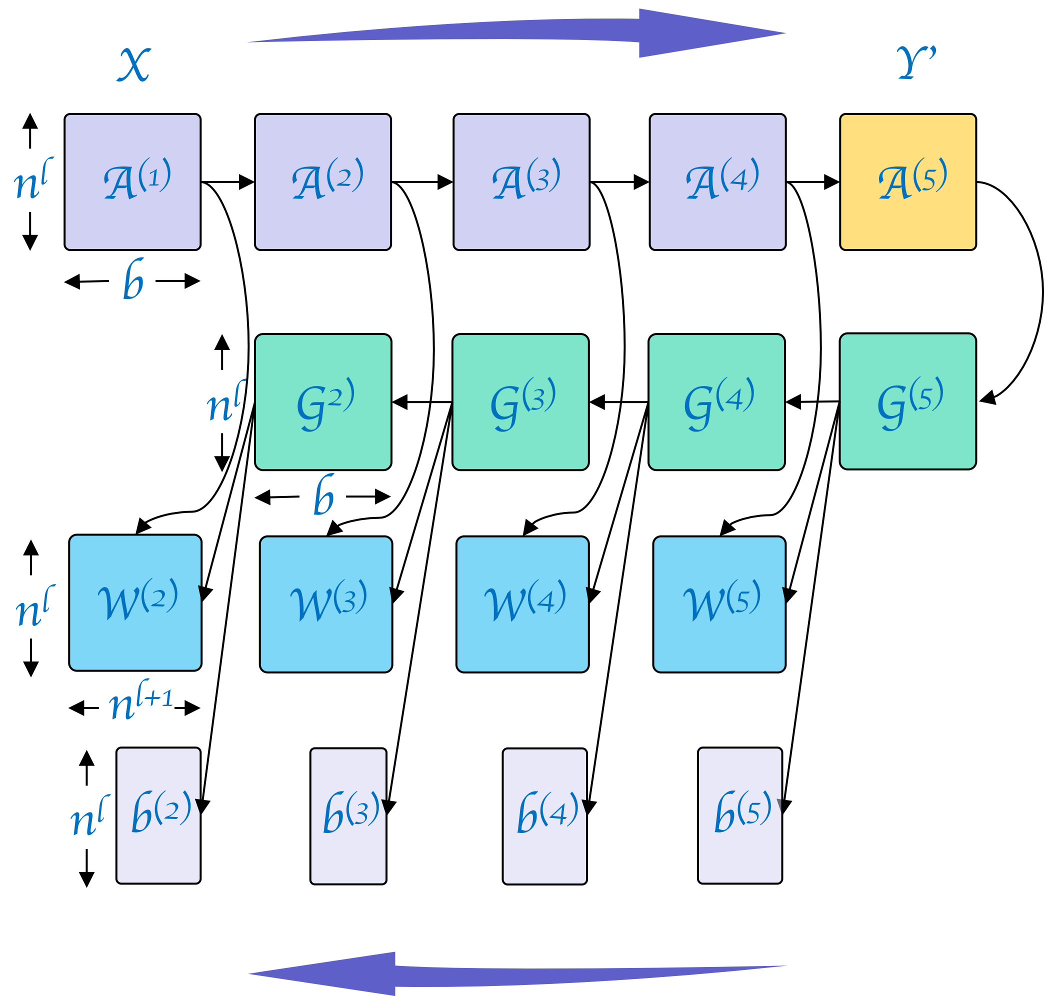
2.1. Gradient computation (GC)

$$G^{(l)} = (W^{(l+1)})^T G^{(l+1)}$$ GEMM

2.2. Weight update (WU)

GEMM

$$W^{(l)} = W^{(l)} - \eta \, G^{(l)} (A^{(l-1)})^T$$



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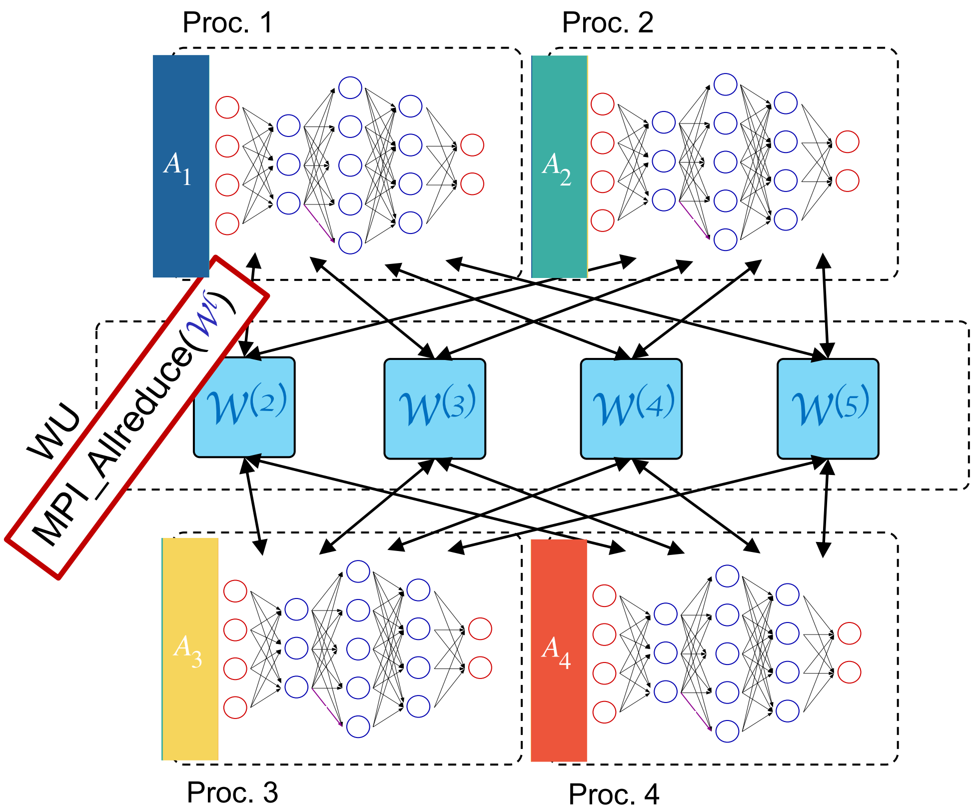
Parallel Training on Clusters

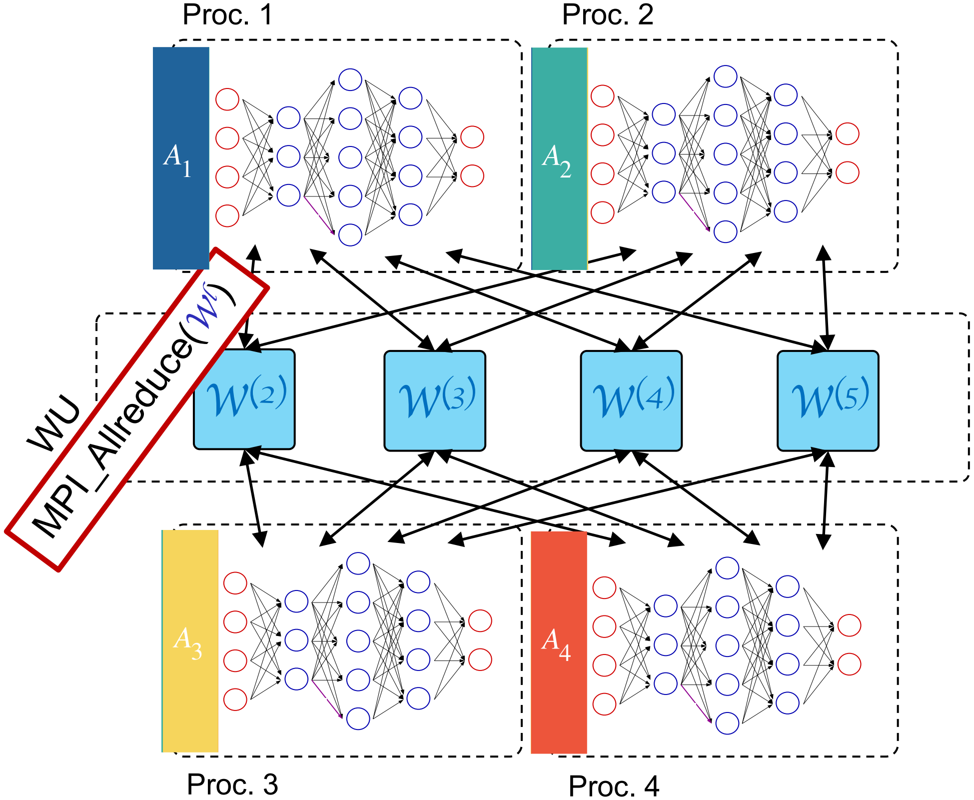
Data parallelism



- Batch size can be increased to feed all processes
- Scalability problems if model does not fit in memory

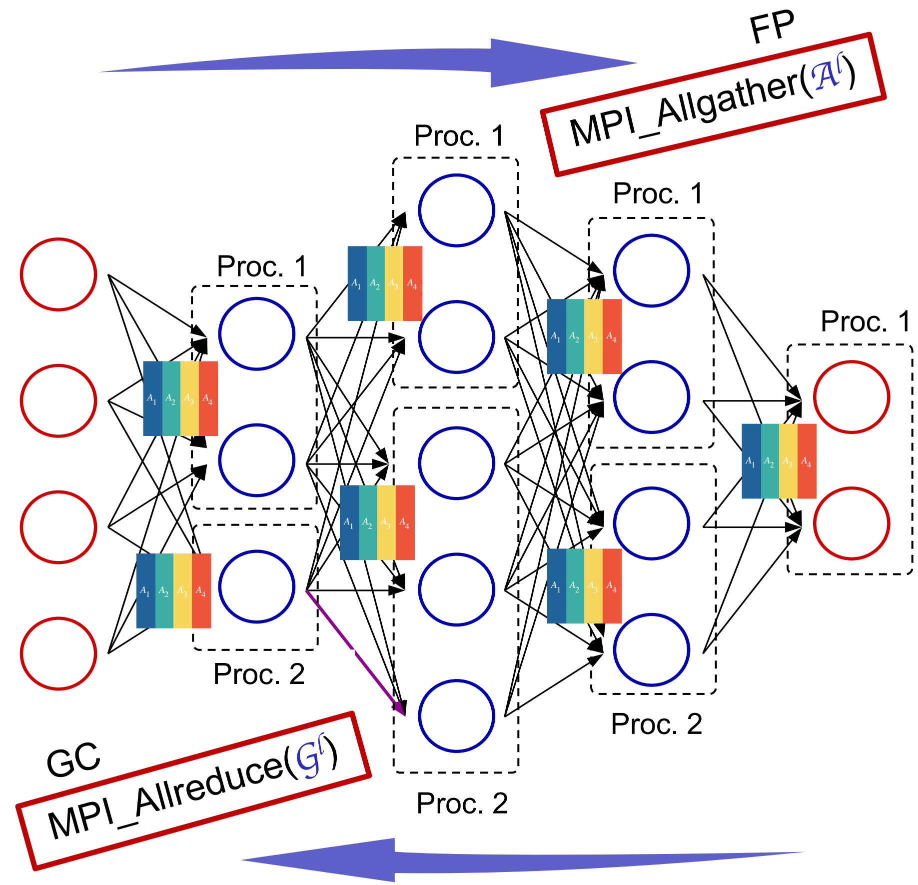
Parallel Training on Clusters

Data parallelism



- Batch size can be increased to feed all processes
- Scalability problems if model does not fit in memory

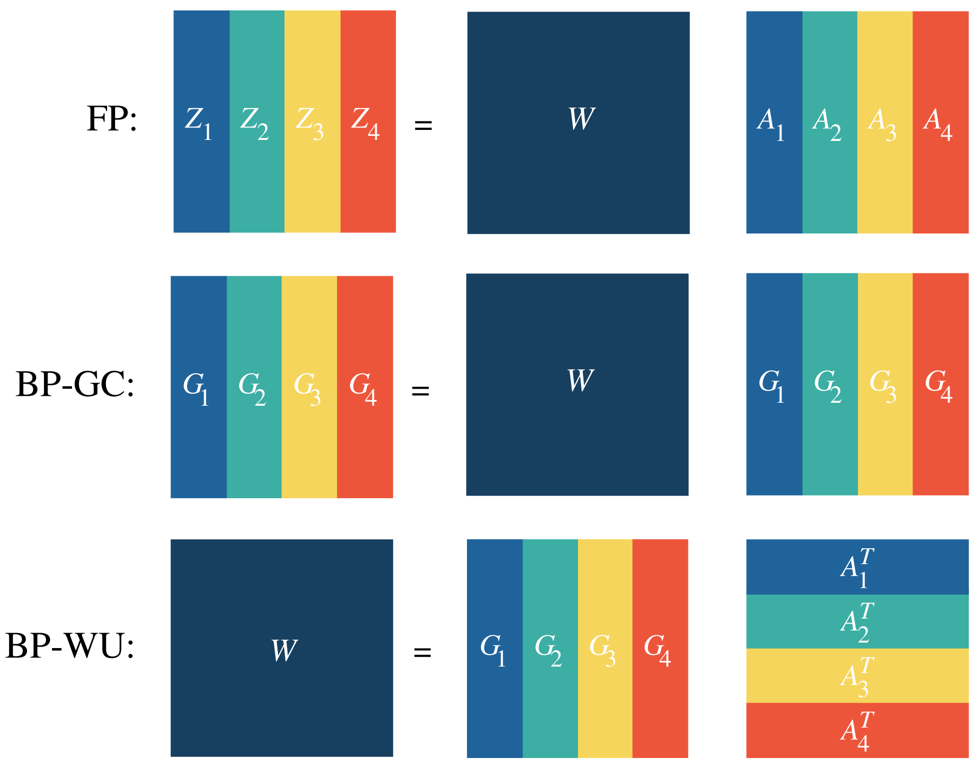
Model parallelism



- Suitable for large models
- More communications required (FP and GC)
- Increasing number of procs will not reduce runtime

Parallel Training on Clusters

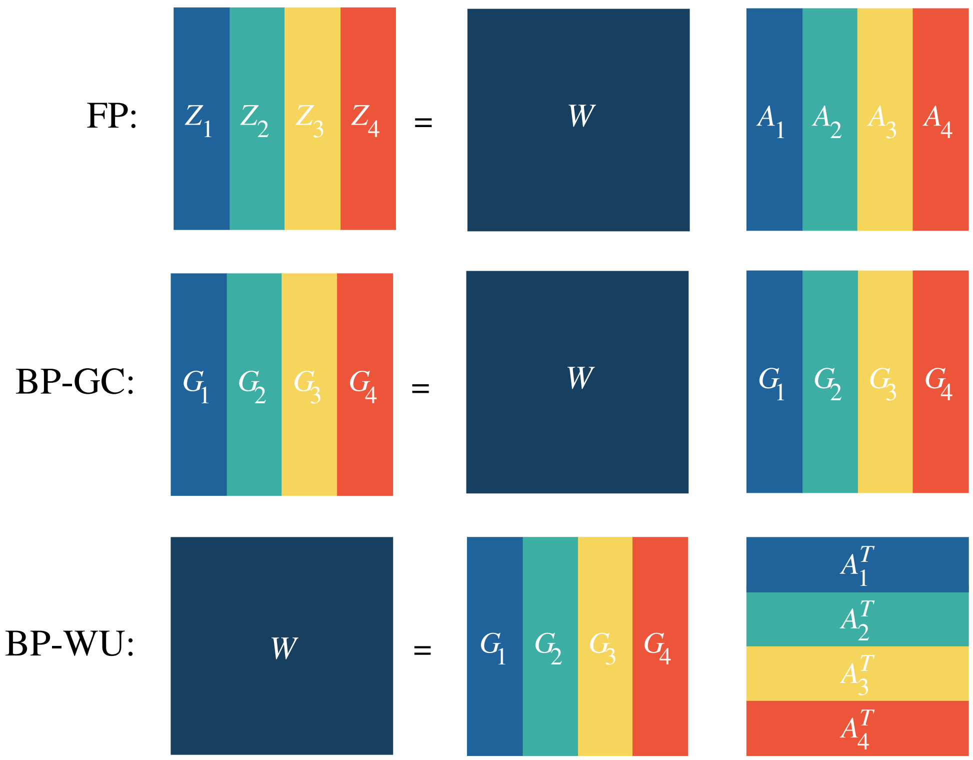
Data parallelism



	C	A	B
FP	$n_l \times b$	$n_l \times n_{l-1}$	$n_{l-1} \times b$
BP-GC	$n_l \times b$	$n_l \times n_{l+1}$	$n_{l+1} \times b$
BP-WU	$n_l \times n_{l-1}$	$n_l \times b$	$b \times n_{l-1}$

Parallel Training on Clusters

Data parallelism



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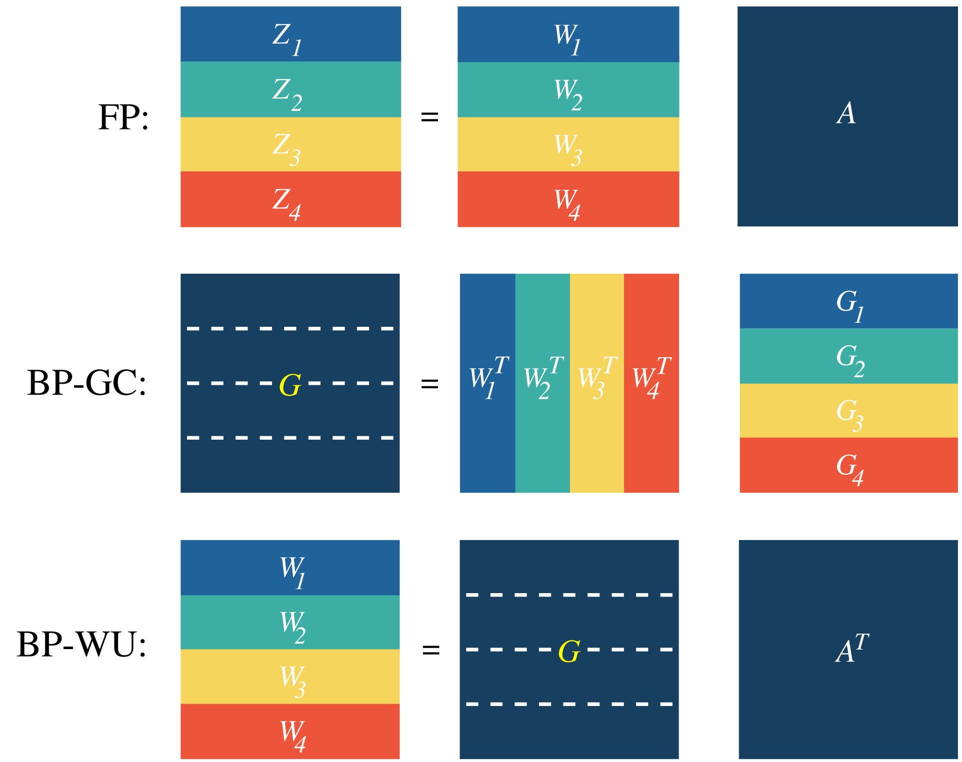

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Parallel Training on Clusters

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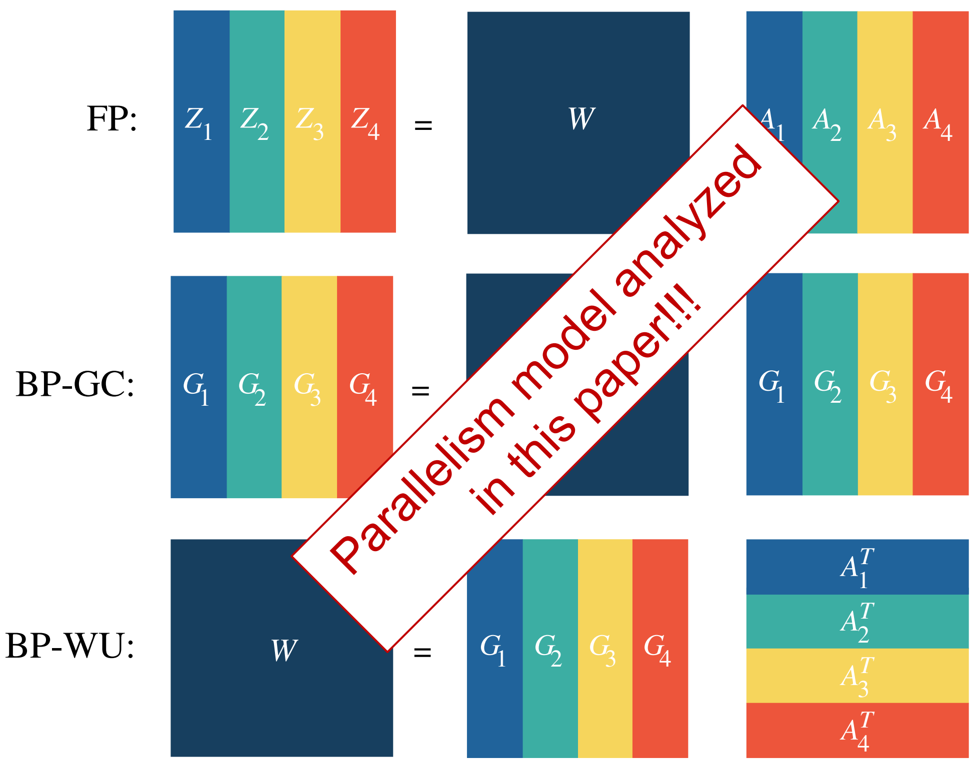
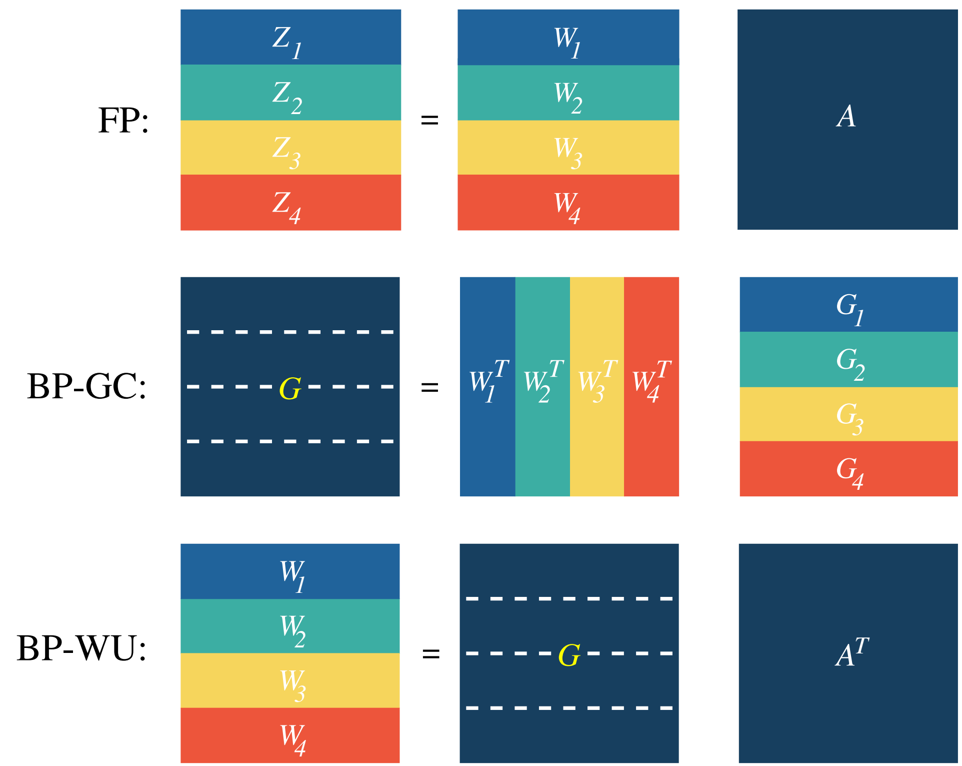


Model parallelism



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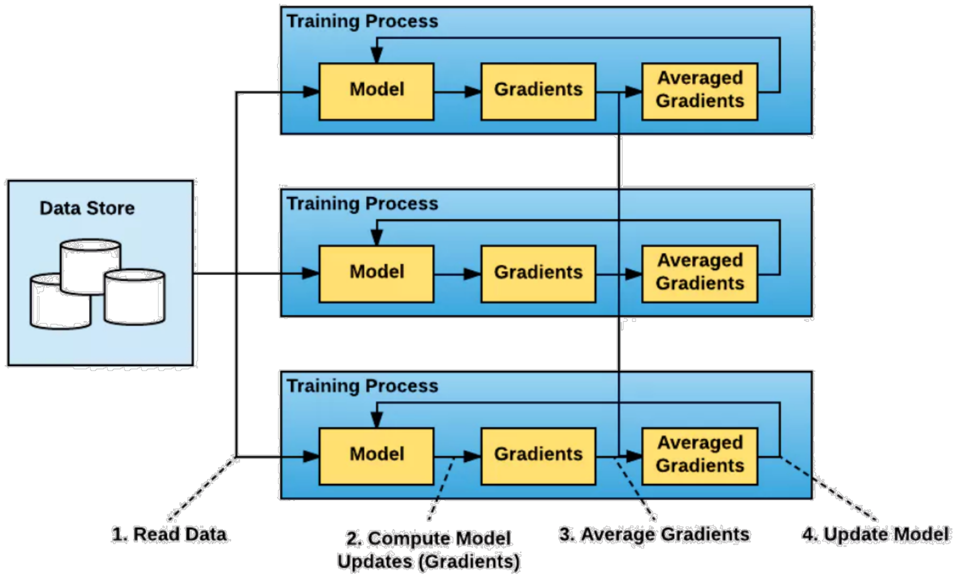
Parallel Training in Clusters

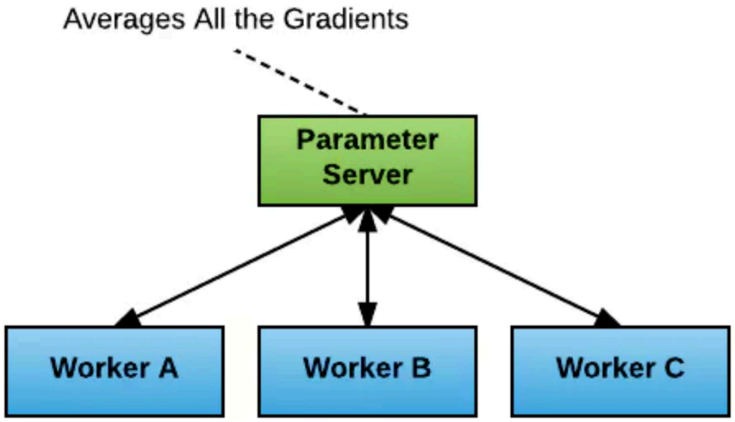
Data parallelism: Communication during BP

- For SGD, weight updates (gradients) must be communicated across all nodes

- Synchronous (e.g., Uber's Horovod)
  - Requires Allreduce operation



- Asynchronous (e.g., distributed TF)
  - Usually, via a parameter server which receives updates, aggregates them, and broadcasts them back



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Performance Model

Model distributed data parallel training, considering:

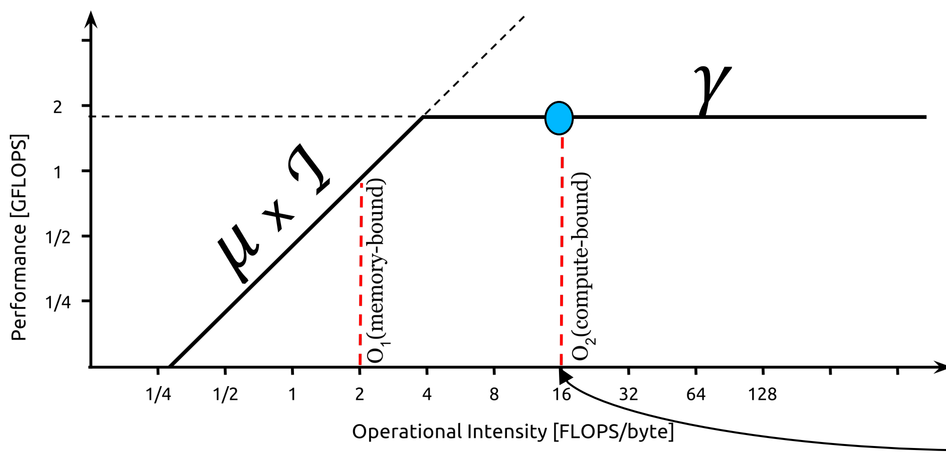
- Neural network model: CNNs of reference in our experiments
- Parallel cluster: $\mathcal{P}$ nodes offering γ FLOPS and μ bytes/s of mem. bandwidth
- Interconnect: Star (all-to-all) and 2D mesh cluster topologies with a latency of α and bandwidth of β bytes/s

Parameter	Meaning
L	Number of layers in the NN.
n_{l-1}, n_l	Number of inputs, outputs in layer l.
k_l^w, k_l^h	Kernel width, height of layer l (only CONV).
c_l	Number of kernels (channels) in layer l (only CONV).
b	Batch size.
δ	Bytes per floating-point number.
P	Number of nodes in the parallel cluster.
γ	Theoretical peak performance (in FLOPS).
μ	Memory bandwidth (in bytes/s).
α	Link latency (in s).
β	Link bandwidth (in bytes/s).

Performance Model

Node performance:

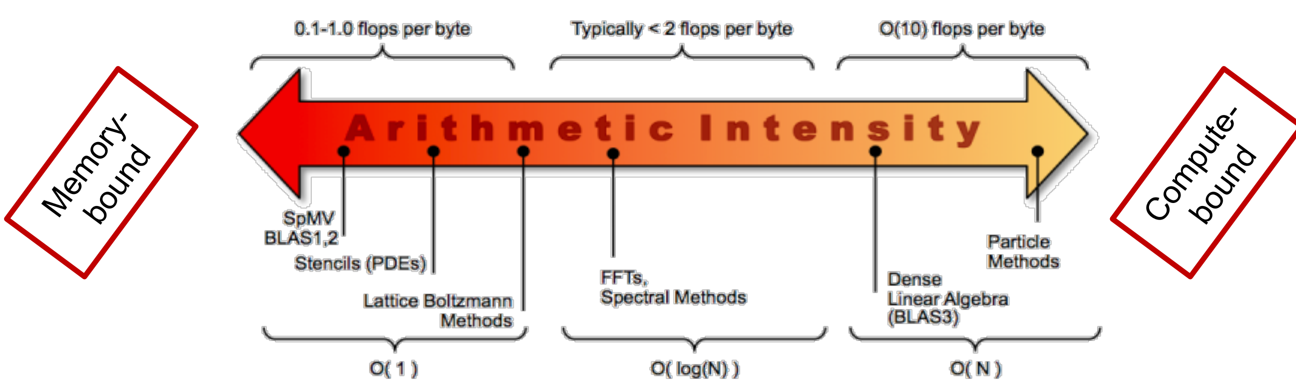
- Roofline model: calculate performance by using the arithmetic intensity



Example: GEMM

$$I_{\text{FP/FC}} = \frac{2 n_l n_{l-1} b}{(n_l b + n_{l-1} b + n_l n_{l-1})\delta} \text{ flops/byte}$$

Estimated execution time = flops / min(μ x $\mathcal{I}$, GFLOPS)

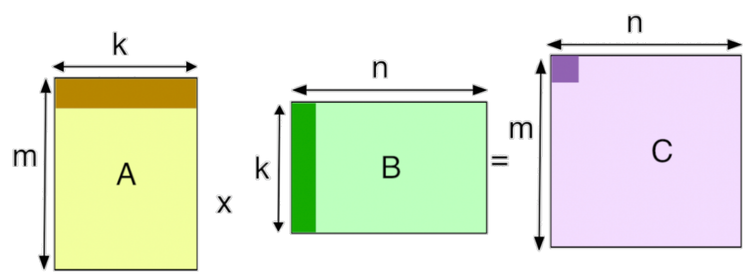


Performance Model

Node performance:

- <u>Roofline model</u>: flops ($2mnk$) / memops ($2mn+mk+nk$) for FC and CONV

FC



	C	A	B
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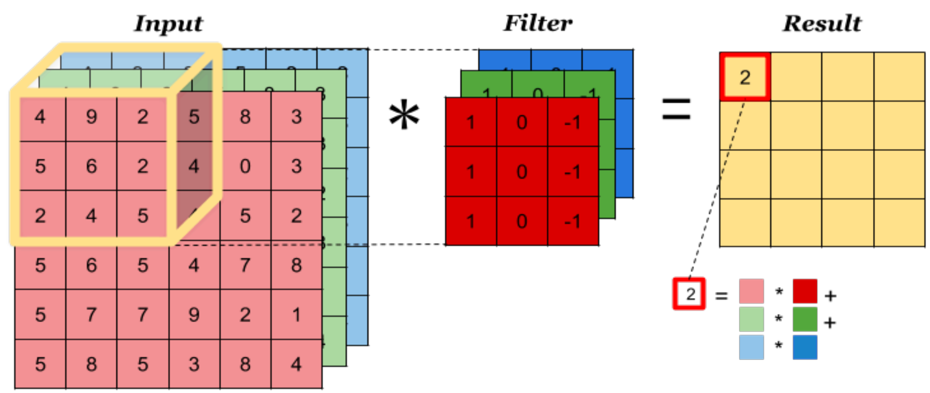
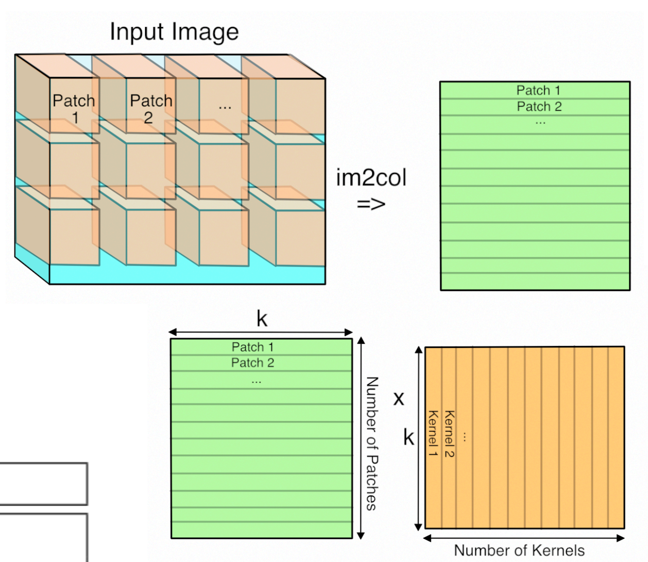
CONV





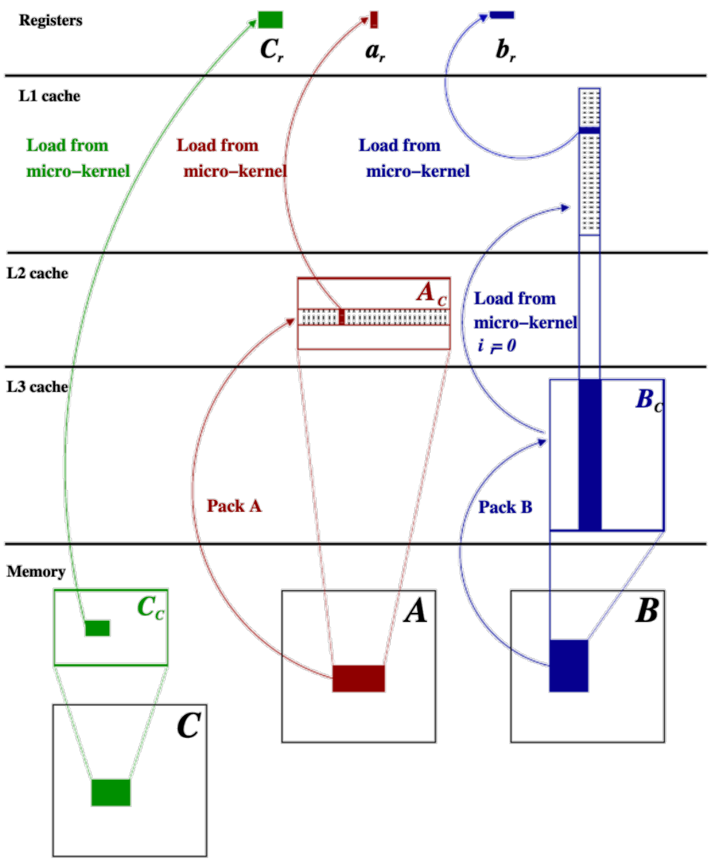
	C	A	B
FP	$b \times c_l \times h_l \times w_l$	$b \times c_{l-1} \times h_{l-1} \times w_{l-1}$	$c_l \times c_{l-1} \times h'_l \times w'_l$
BP-GC	$b \times c_l \times h_l \times w_l$	$b \times c_{l+1} \times h_{l+1} \times w_{l+1}$	$c_l \times c_{l+1} \times h'_{l+1} \times w'_{l+1}$
BP-WU	$c_l \times c_{l-1} \times h'_l \times w'_l$	$b \times c_{l-1} \times h_{l-1} \times w_{l-1}$	$b \times c_l \times h_l \times w_l$

Performance Model

Node performance:

- We consider a blocked implementation of GEMM, as it is done in GotoBLAS2, OpenBLAS, BLIS, or Intel MKL
- Partitioning according to a specific level of cache hierarchy (OpenBLAS and BLIS)
  - m, n, k are reduced to m_c, n_c, k_c so that B_c fits in L3, A_c fits in L2, and C to RAM

for $j_c = 0, 1, \ldots, n-1$ **in steps of** n_c
  for $p_c = 0, 1, \ldots, k-1$ **in steps of** k_c
    $B(p_c : p_c + k_c - 1, j_c : j_c + n_c - 1) \rightarrow B_c$
    for $i_c = 0, 1, \ldots, m-1$ **in steps of** m_c
      $A(i_c : i_c + m_c - 1, p_c : p_c + k_c - 1) \rightarrow A_c$
      // Macro-kernel
      $C_c(i_c : i_c + m_c - 1, j_c : j_c + n_c - 1)$
       $+= A_c(i_c : i_c + m_c - 1, p_c : p_c + k_c - 1)$
       $\cdot\ B_c(p_c : p_c + k_c - 1, j_c : j_c + n_c - 1)$
    endfor
  endfor
endfor



- Intensity is then computed as:

$$I_{\mathrm{FP/FC}} = \frac{2 m_c n_c k_c}{(m_c n_c + m_c k_c + k_c n_c)\delta}$$

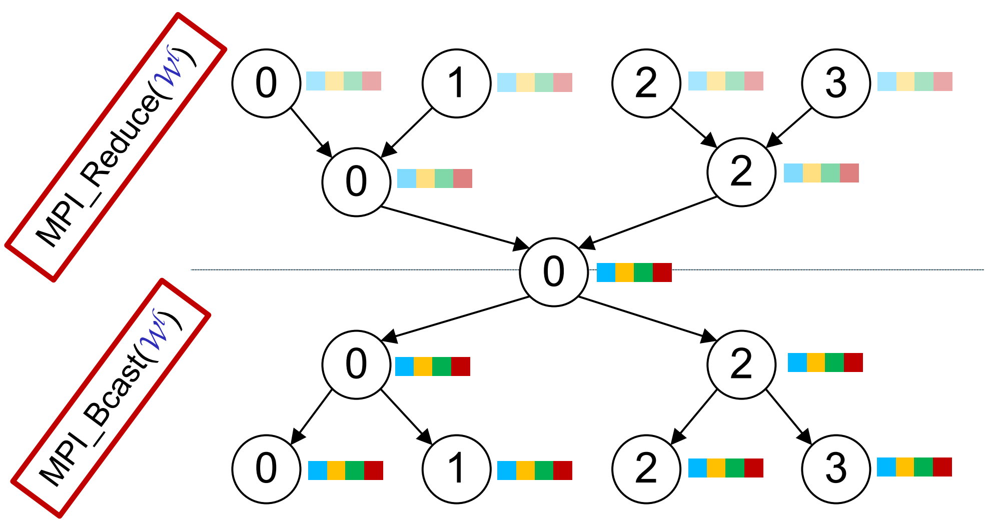
Performance Model

Network transmission performance (MPI_Allreduce):

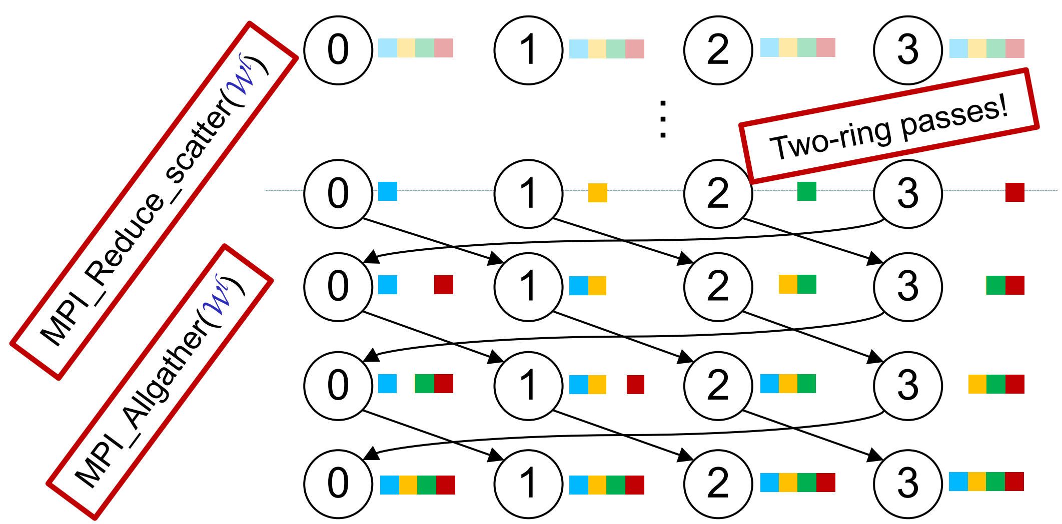
- <u>Allreduce</u>: Minimum spanning tree (MST) and Bucket (BKT)

Topology	Star		Mesh	
Algorithm	Latency	Communication	Latency	Communication
MST	$2\lceil \log_2 P \rceil (\alpha_1 + \alpha_3)$	$2\lceil \log_2 P \rceil \frac{s\delta}{\beta}$	$2\sum_{k=0}^{d-1} \lceil \log_2 d_k \rceil (\alpha_1 + \alpha_3)$	$2\sum_{k=0}^{d-1} \lceil \log_2 d_k \rceil \frac{s\delta}{\beta}$
BKT	$2P\alpha_1$	$2\frac{(P-1)}{P}\frac{s\delta}{\beta}$	$2\sum_{k=0}^{d-1} d_k \alpha_1$	$2\frac{(P-1)}{P}\frac{s\delta}{\beta}$

<u>MST</u> (Reduce + Broadcast)



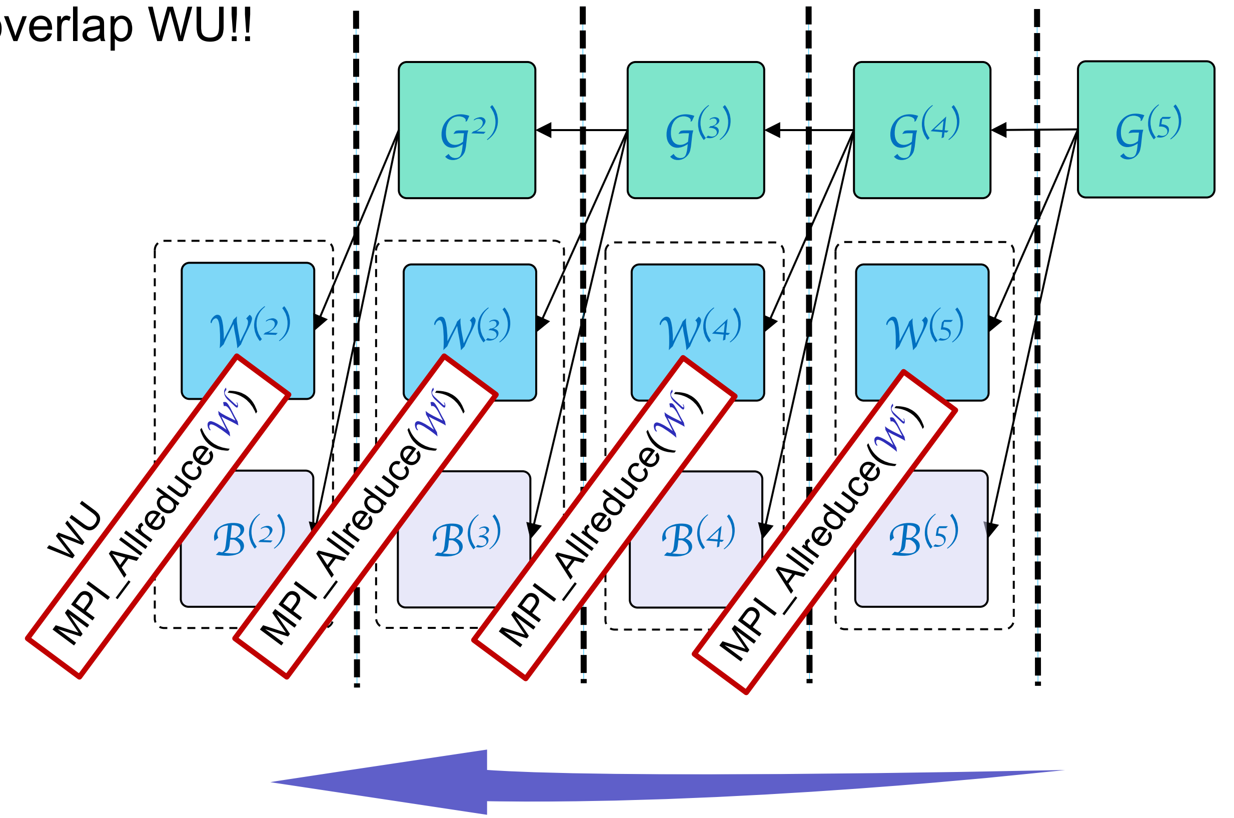
<u>BKT</u> (Reduce-Scatter + Allgather)



Performance Model

Overlapping communication with computation in BP:

- Strict data dependencies: FP: $\mathcal{A}^{(2)} \rightarrow \mathcal{A}^{(2)} \rightarrow \ldots\ \mathcal{A}^{(\mathcal{L})}$; GC: $\mathcal{G}^{(\mathcal{L})} \rightarrow \mathcal{G}^{(\mathcal{L}\text{-}1)} \rightarrow \ldots\ \mathcal{G}^{(2)}$
- But MPI_Allreduce($\mathcal{W}^{(l)}$) can be performed in parallel with $\mathcal{G}^{(\mathcal{L}\text{-}1)}, \mathcal{G}^{(\mathcal{L}\text{-}2)}, \ldots, \mathcal{G}^{(2)}$
  - GC can overlap WU!!



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Results

CNN models:

Model	FC	CONV	POOL	Total
AlexNet	3	5	3	11
Inception v3	1	94	14	109
ResNet-50 v2	1	53	1	55
VGG16	3	13	5	21

SKYLAKE cluster parameters:

Parameters	SKYLAKE cluster
# of Nodes	1,000
Interconnect	Dual-rail Mellanox EDR Infiniband
Link bandwidth (Gbps)	200
Max. link latency (μs)	0.5

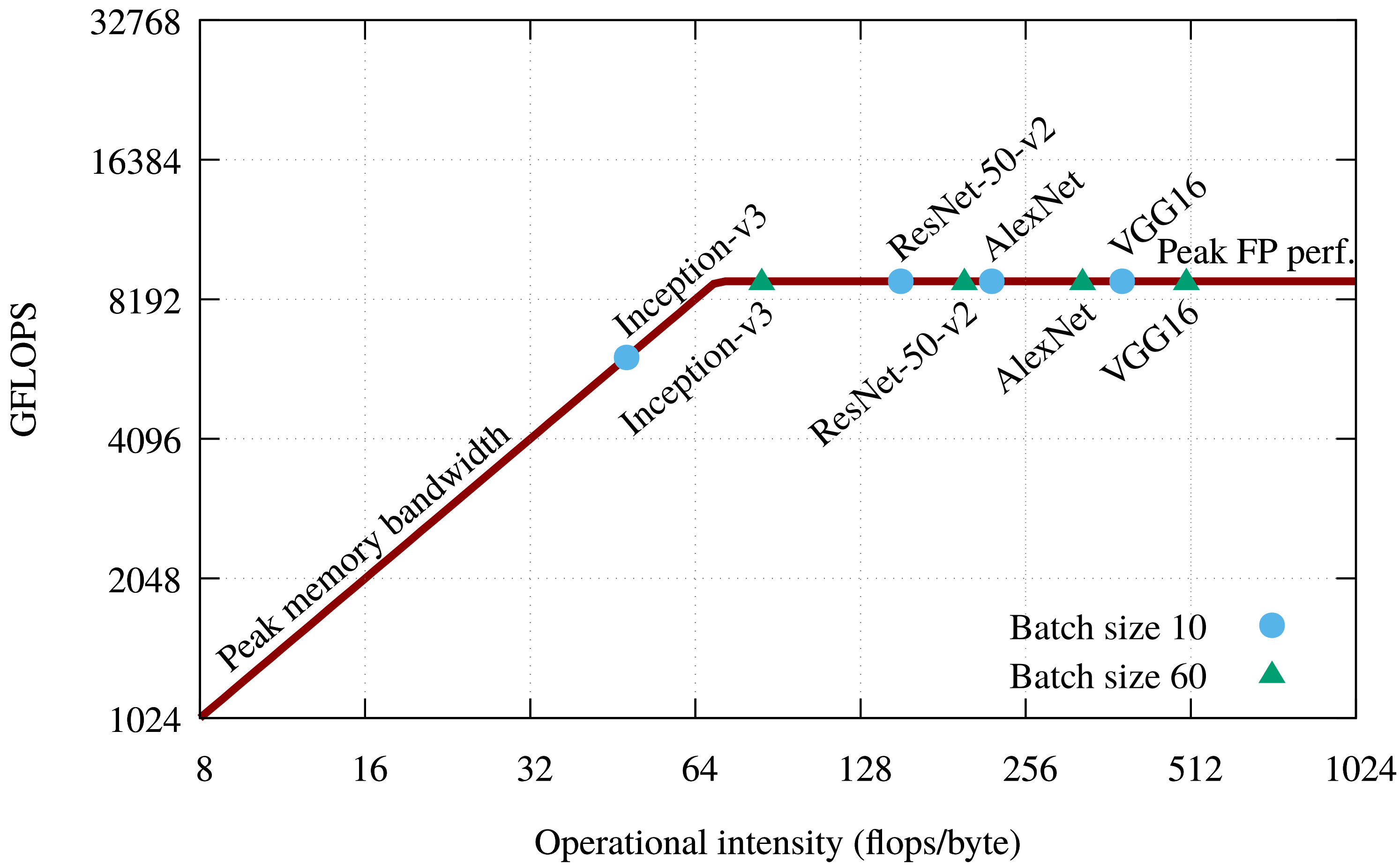
SKYLAKE node parameters:

Parameters	SKYLAKE node
Processor model	Intel Xeon Platinum 8180M
Max. FP32 throughput (flops/cycle)	64
Frequency (GHz)	2.5
# of Cores	28 (56 2-way SMT)
Peak FP32 performance (GFLOPS)	8,960
Mem. bus width (Bytes)	8
Mem. clock rate (GHz)	2.666
Mem. channels	6
Peak mem. bandwidth (GBytes/s)	128
DDR4 RAM memory (GBytes)	256

BLIS GEMM on a SKYLAKE Intel processor: m_c^o = 480, n_c^o = 3072, and k_c^o = 384

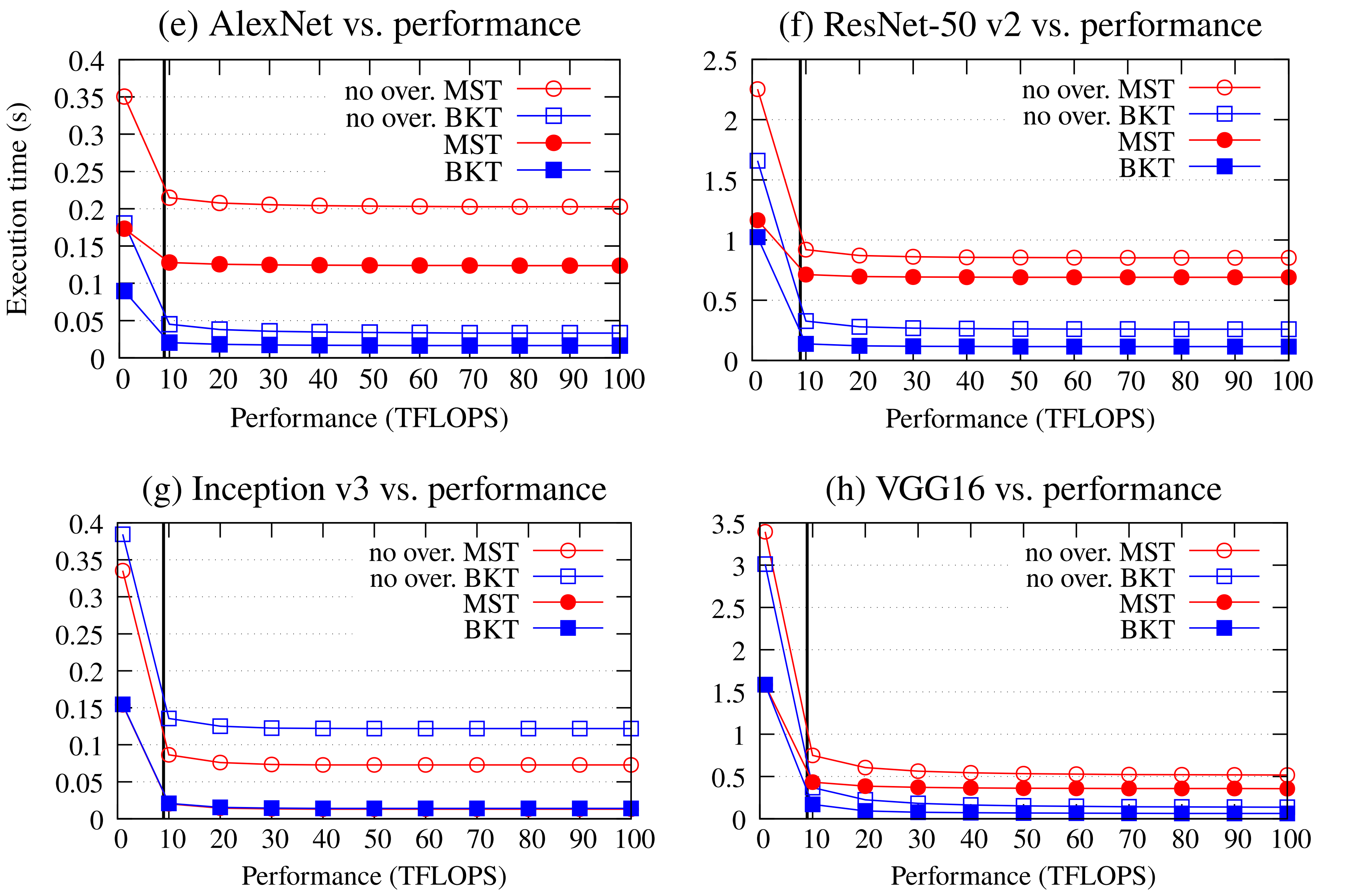
Arithmetic intensity of CNNs

- Batch size 10 and 60 samples per process, i.e., 10k and 60k samples in total

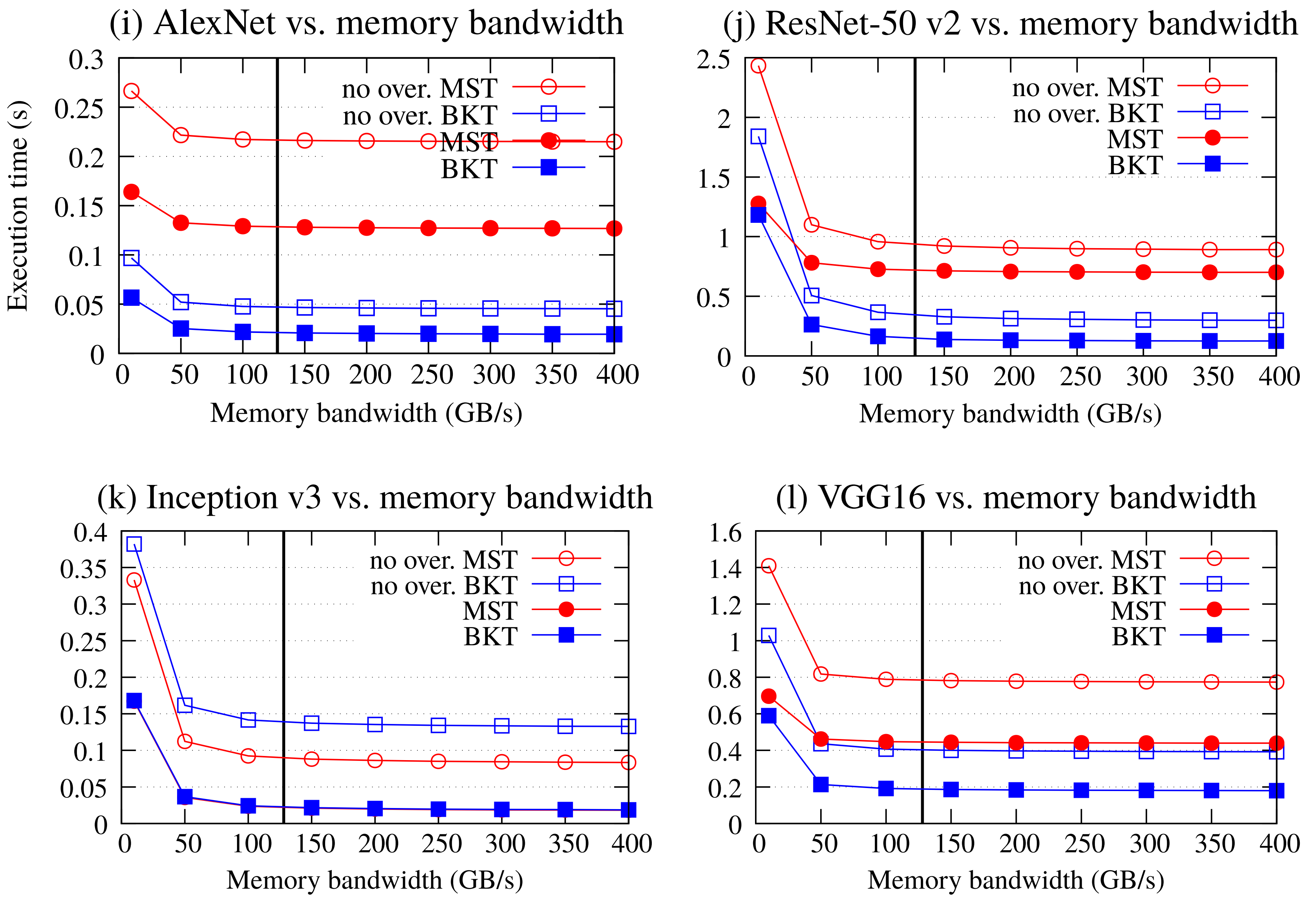


Most CNNs are compute bound, except for Inception-v3 with batch size 10k

Performance of distributed training



Performance of distributed training



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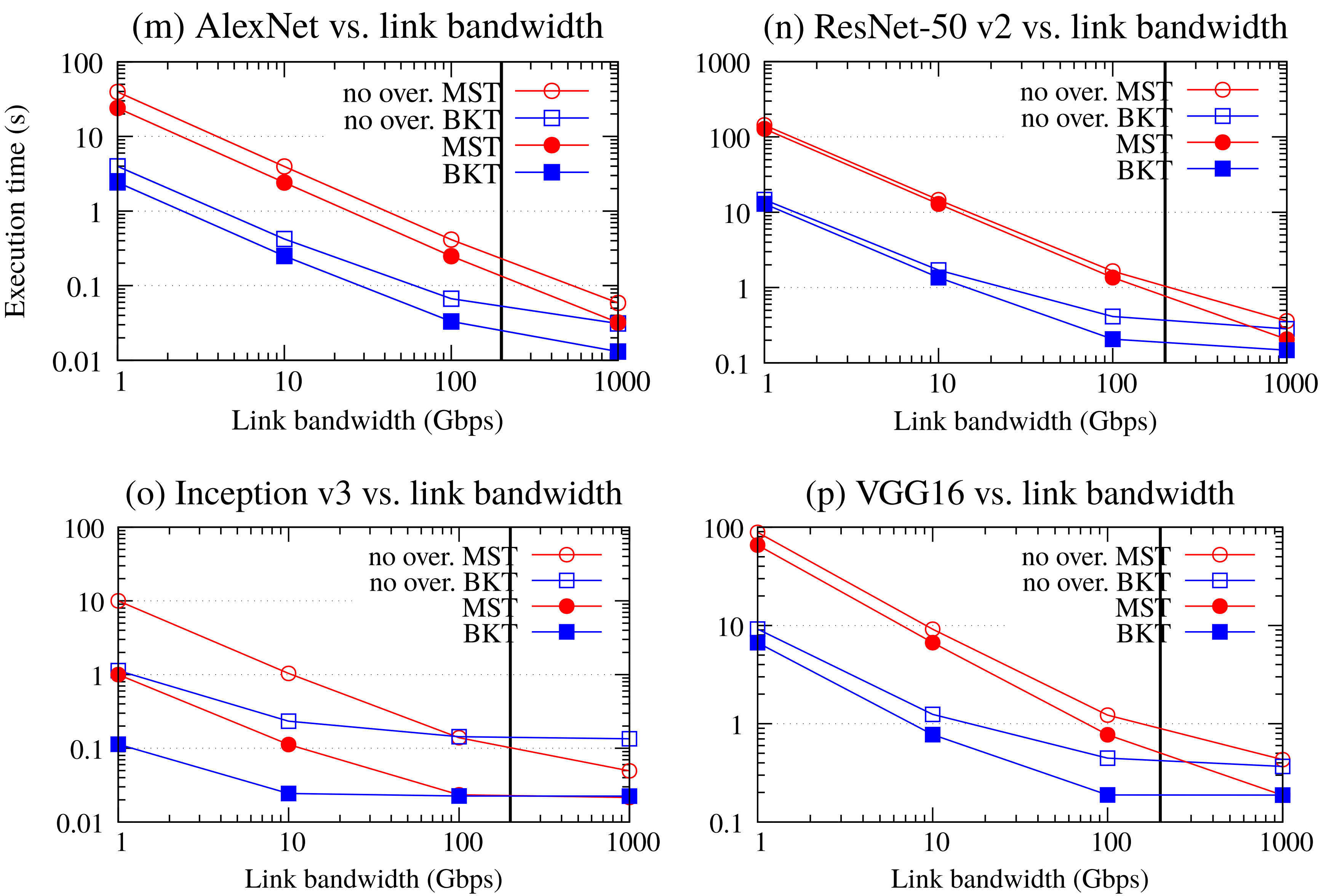

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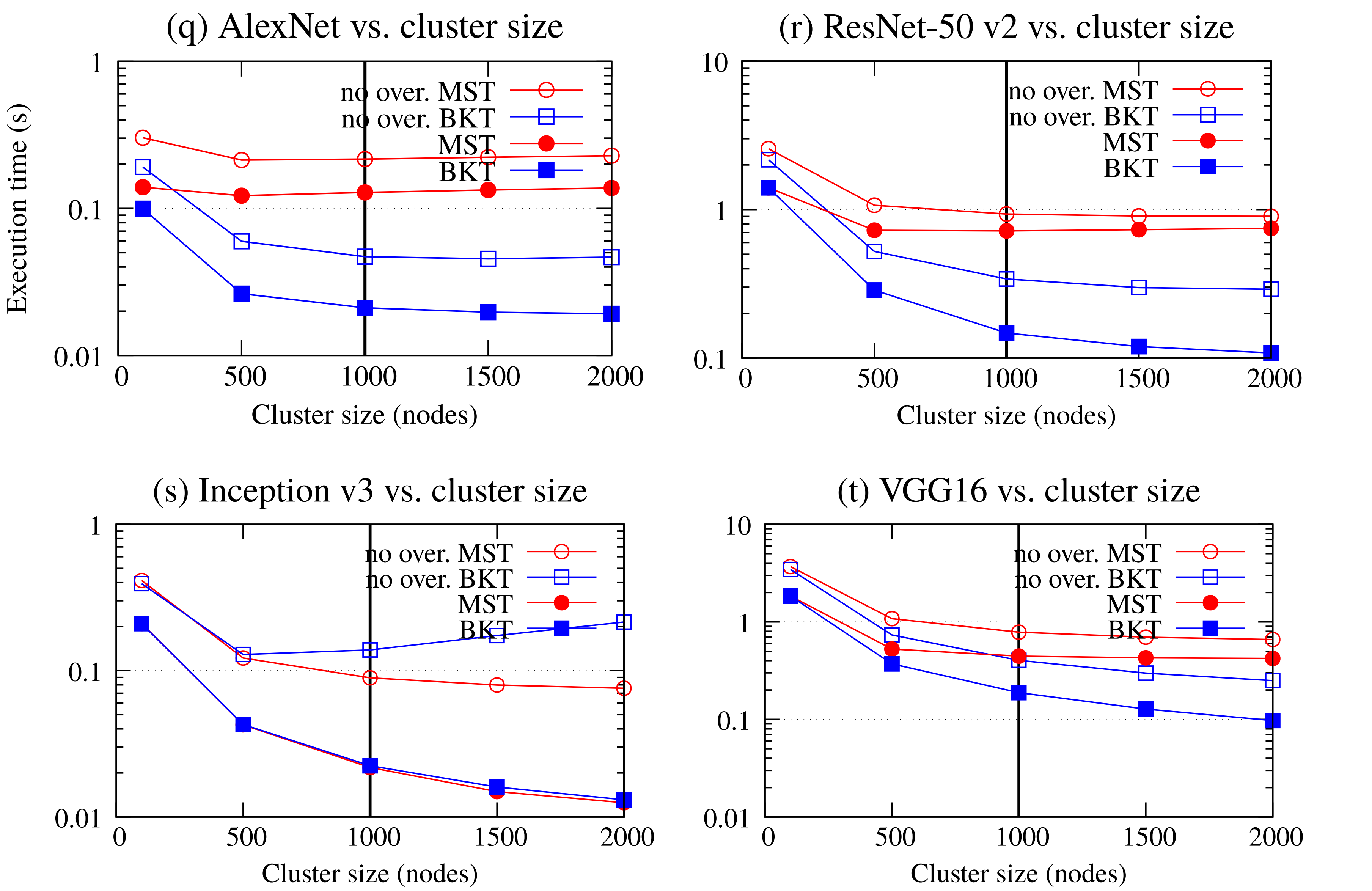

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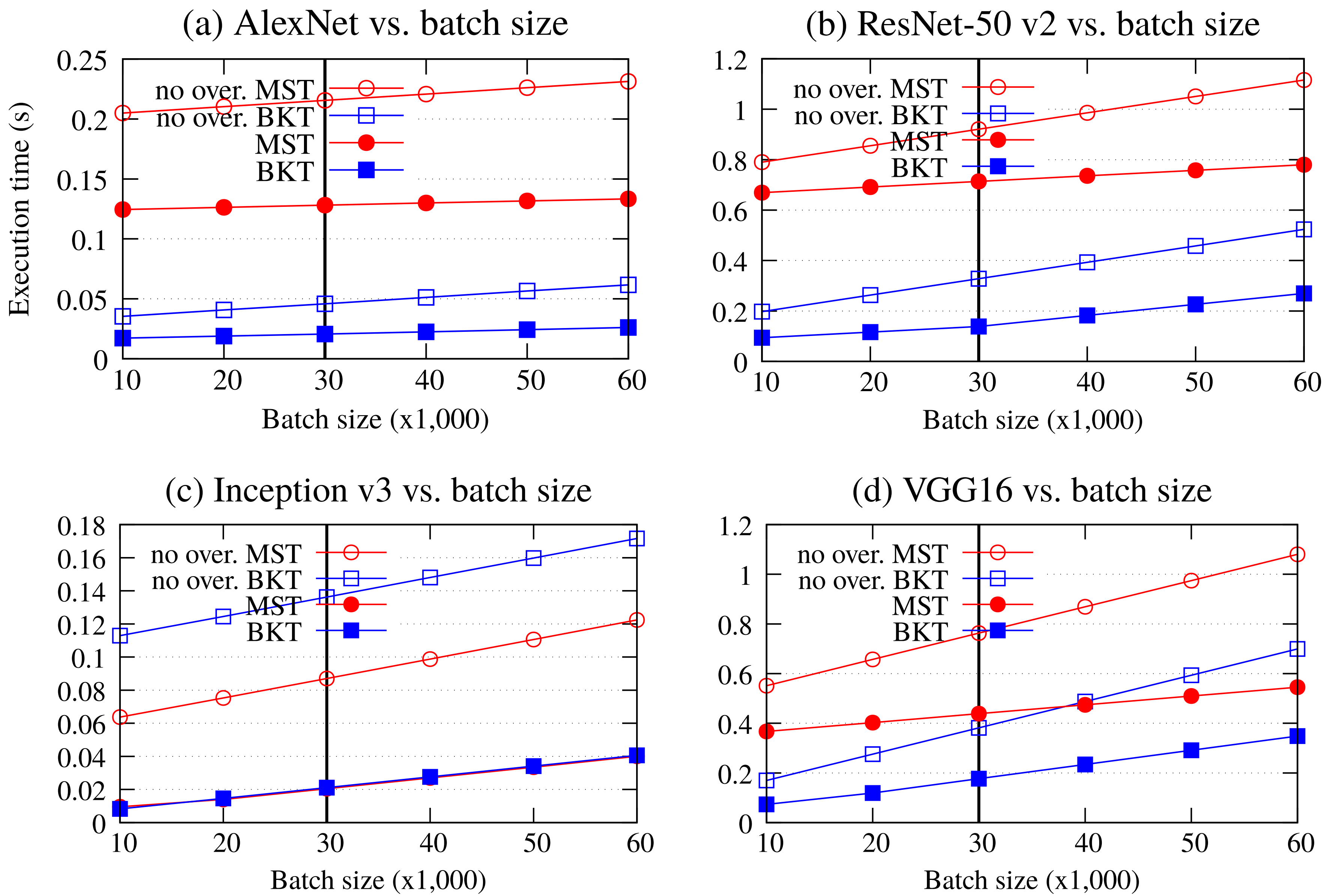

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Conclusions

- Current CNN models are mainly compute-bound:
  - Improving the processor capabilities does not bring noticeable improvements
- Overlapping communication with computation increases the performance!
- Network is important: increasing link bandwidth may reduce the execution time of collective operations
- Larger mini-batches provide a more accurate estimate of the gradients and accelerate the optimization process, however each step requires longer computations
  - However, increasing mini-batch size can hurt test accuracy!

Thank you for your attention!

Questions?