Delayed Weight Update for Faster Convergence in Data-parallel Deep Learning

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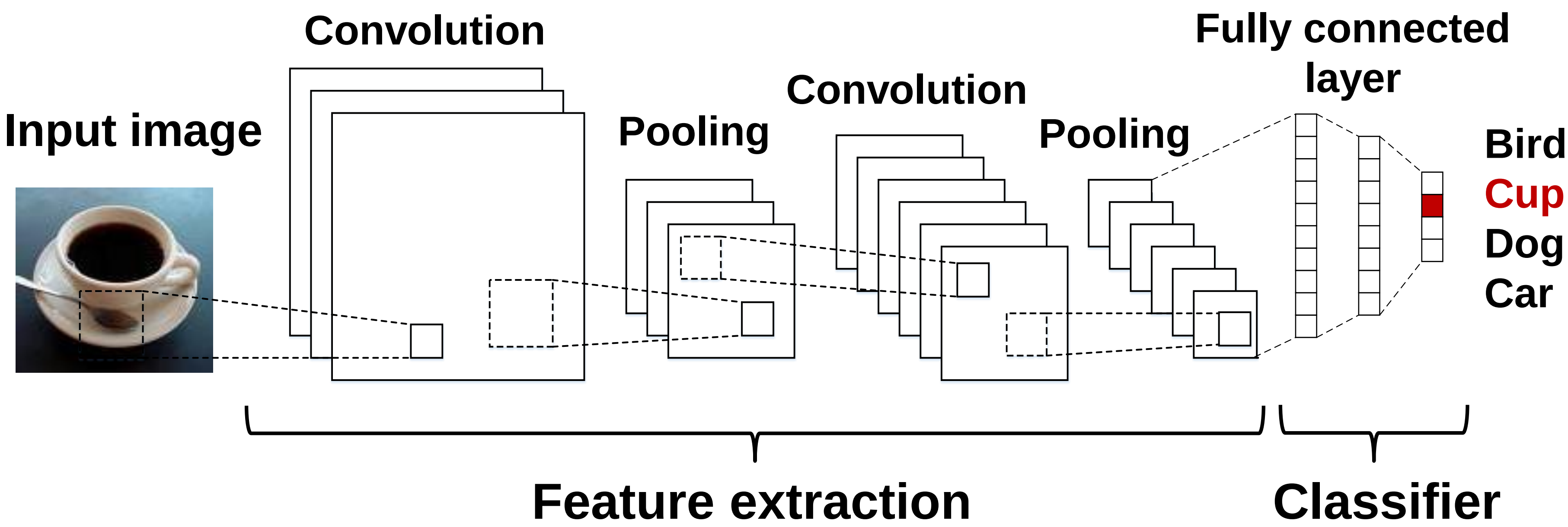
Outline

1. Introduction
   a. Deep learning
   b. Parallelization for deep learning
2. Proposed data-parallelism
3. Experimental result
4. Conclusion

Background: Deep learning

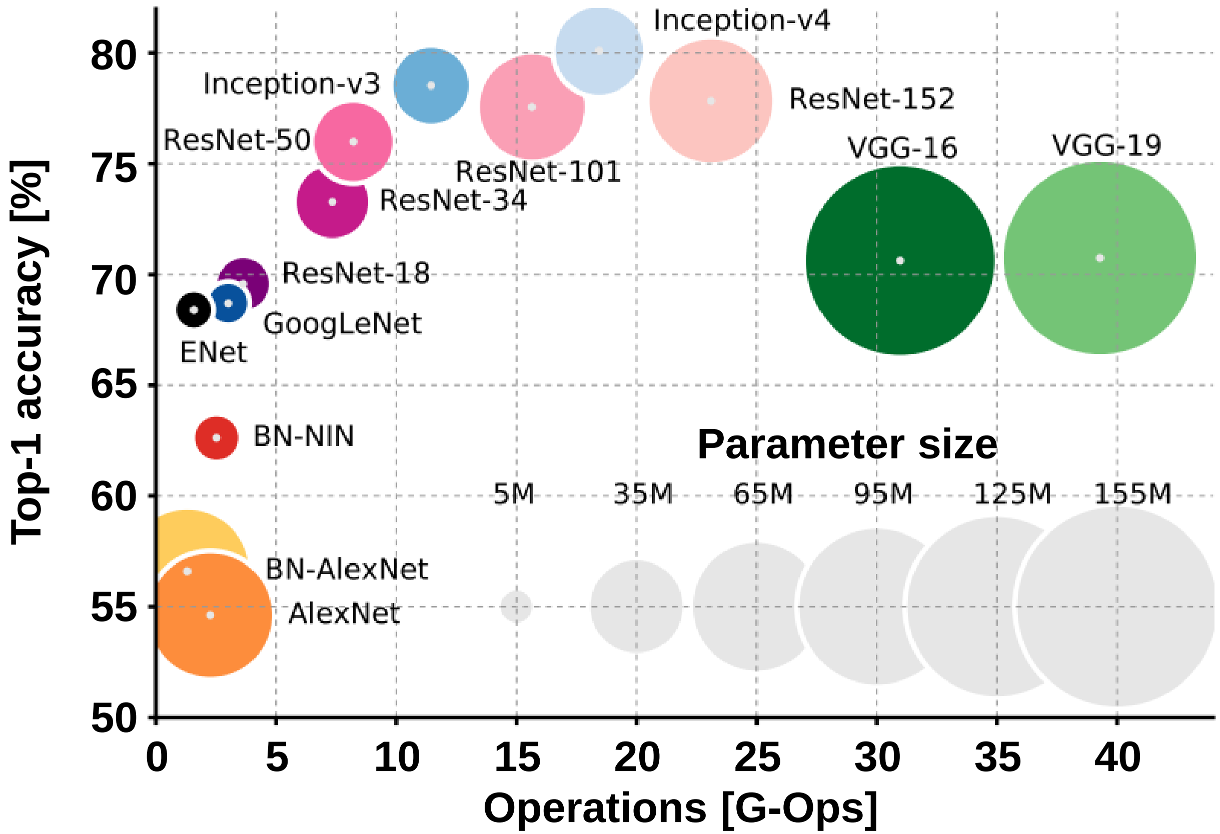
- Deep learning has succeeded in various tasks with different kinds of data by changing the form
  - Convolutional Neural Network for image data
  - Recurrent Neural Network for time series data
  - Deep Q Network for playing video game
  - etc…

- Convolutional Neural Network (CNN)



Background: CNN

- **ImageNet Large Scale Visual Recognition Challenge (ILSVRC)**

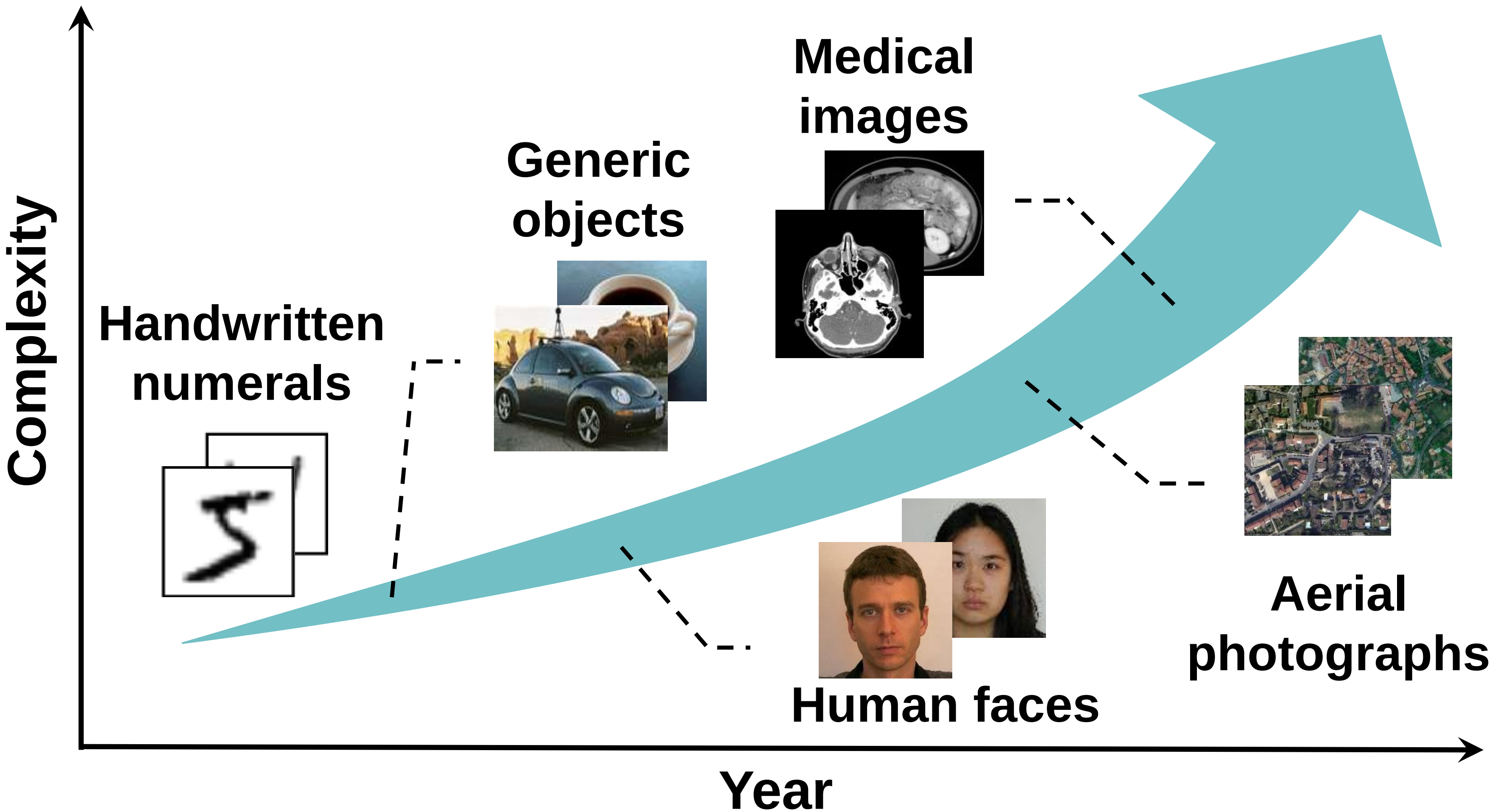


The evolution of the algorithm made it possible to deepen the model.

- **Accuracy improved dramatically, but the amount of computation and parameter exploded in accordance with the number of layers.**

Alfredo Canziani, et al., arXiv:1605.07678, Apr., 2017.

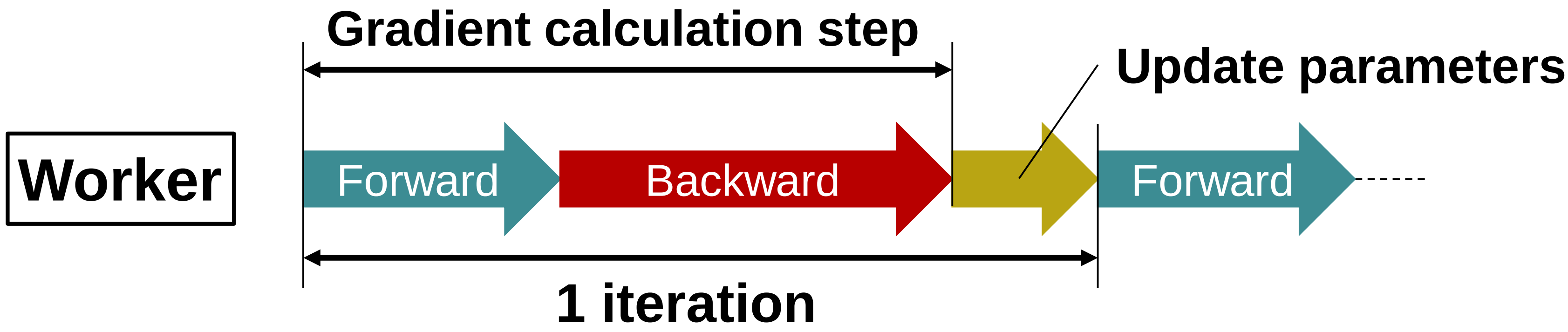
Background: CNN's target



Along with the development, target data gets more complicated. Then the CNN model gets deeper, and so computational complexity will get larger.

Background: CNN's challenge

- **Learning flow w/ single worker**



- **Due to the large amount of computation, devices specialized for matrix computation like GPUs are used.**

- **However, since it is necessary to calculate millions of iterations, it is difficult to learn in realistic time even with such a device.**
  - **Distributed deep learning has received a remarkable amount of attention.**

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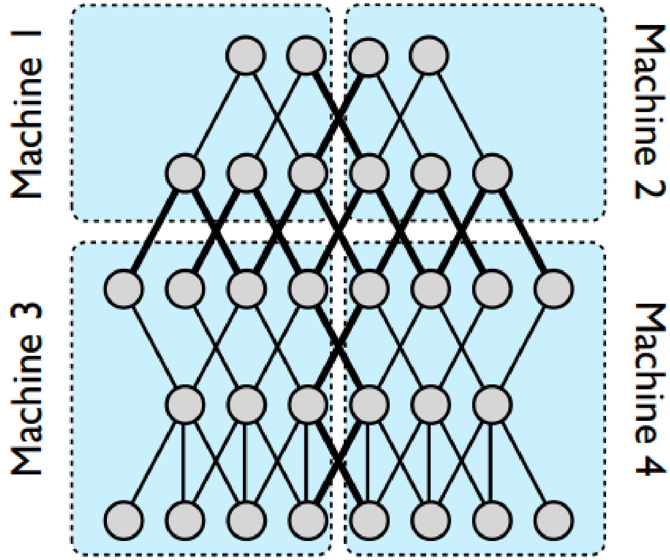
Model parallelism

- Model parallelism divides **dimensions of model**.
  - Each worker calculates the different part of the model.

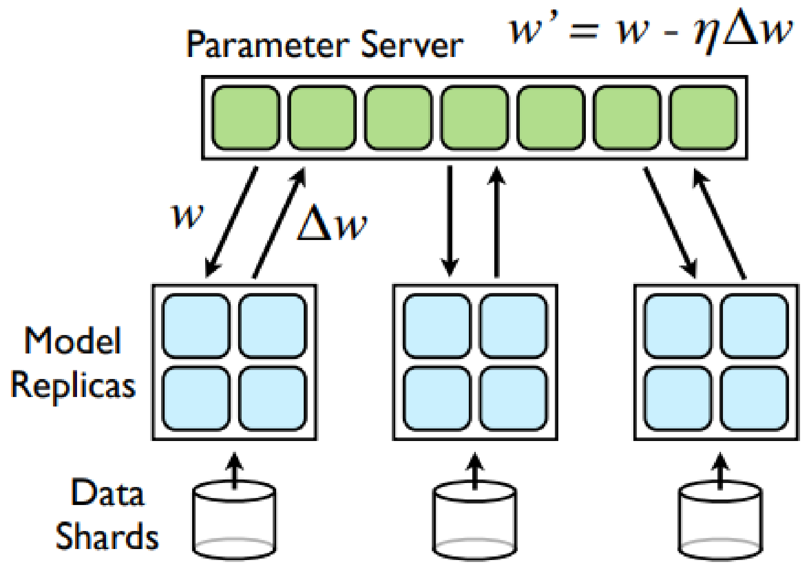


✓ No need for parameter integration
✓ Possibility of a huge model implementation even when the model cannot fit into GPU
× Model-dependent
× Low versatility

Dean, Jeffrey et al. "Large Scale Distributed Deep Networks"

Data parallelism

- Data parallelism divides dimensions of data.
  - Each worker calculates a different batch data.



✓ Simple implementation for homogeneous workers

✓ Dominant method for high versatility

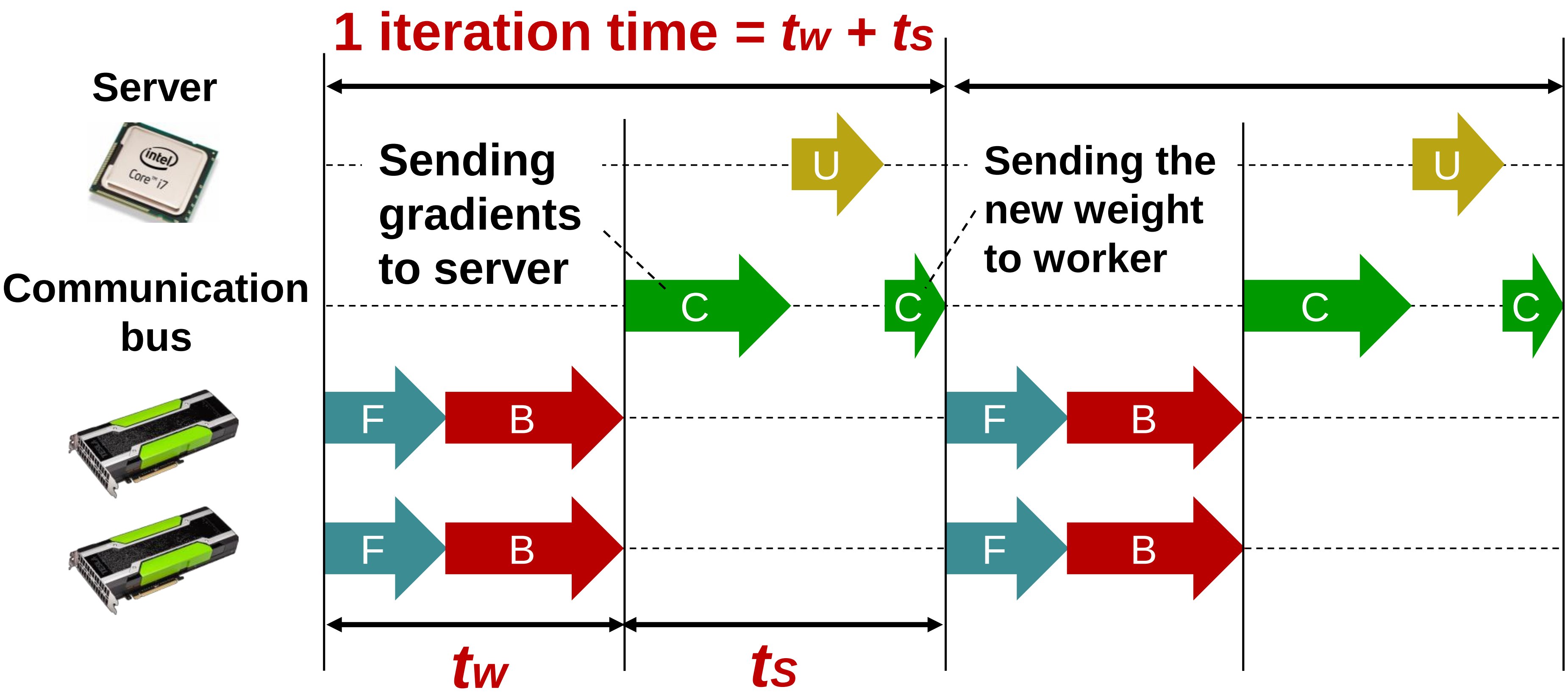
× Need for parameter integration

- For VGG-F network, it is necessary to communicate 60M parameter per thread.

Dean, Jeffrey et al. "Large Scale Distributed Deep Networks"

Data parallelism challenge

- **Data parallel learning flow w/ two GPUs**



For worker, *ts* is the latency for next step. Particulary when the size of gradient is large, communication latency becomes bottleneck.

➢ **Our target is to <u>eliminate this communication latency</u>.**

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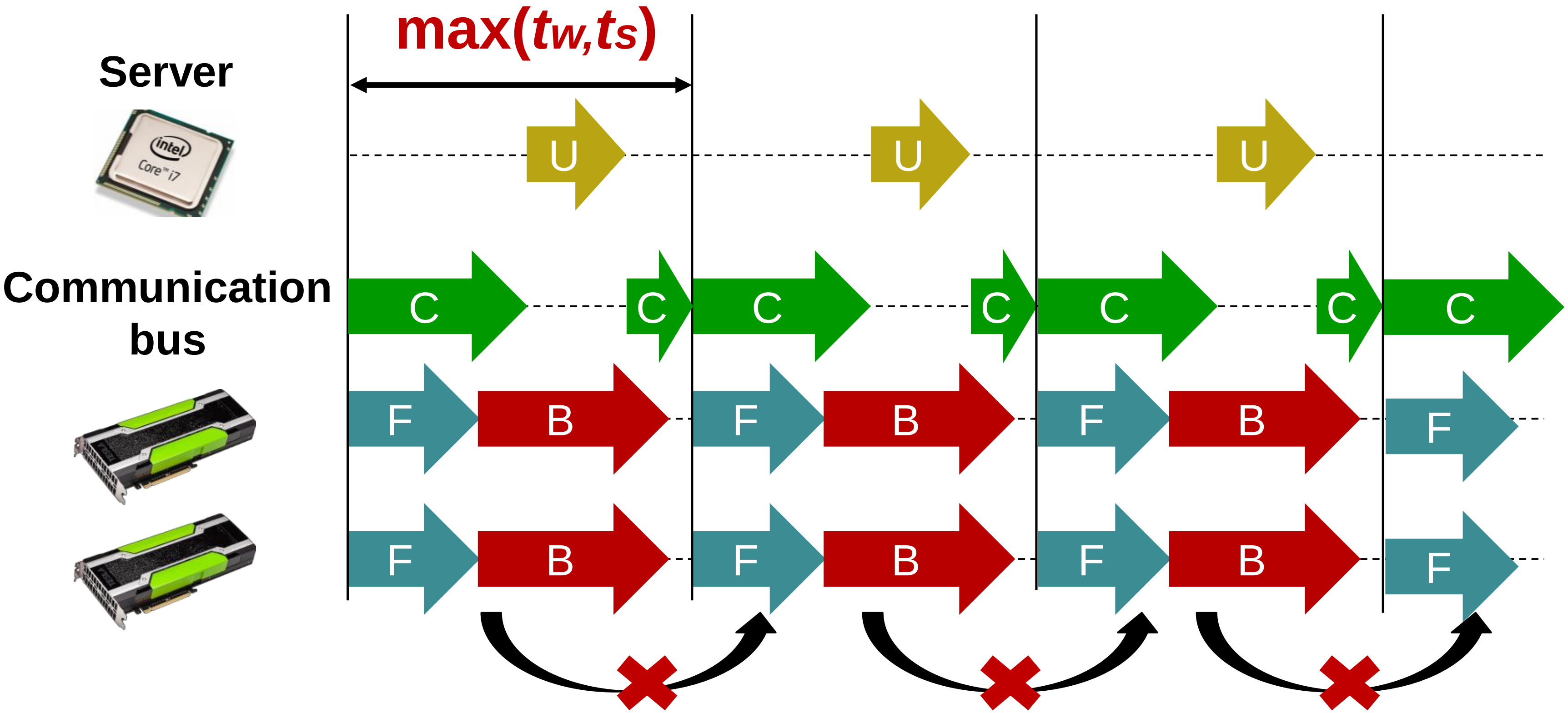
Proposed method

- In the conventional data parallel method, workers need to wait until they receive the new weight.
  - When the weight size is large, communication latency hinders speeding up by parallelism.

- Then, we proposed a method
  - to calculate the gradient using weights delayed by one step.
  - to overlap the communication with the gradient calculation.

Proposed method

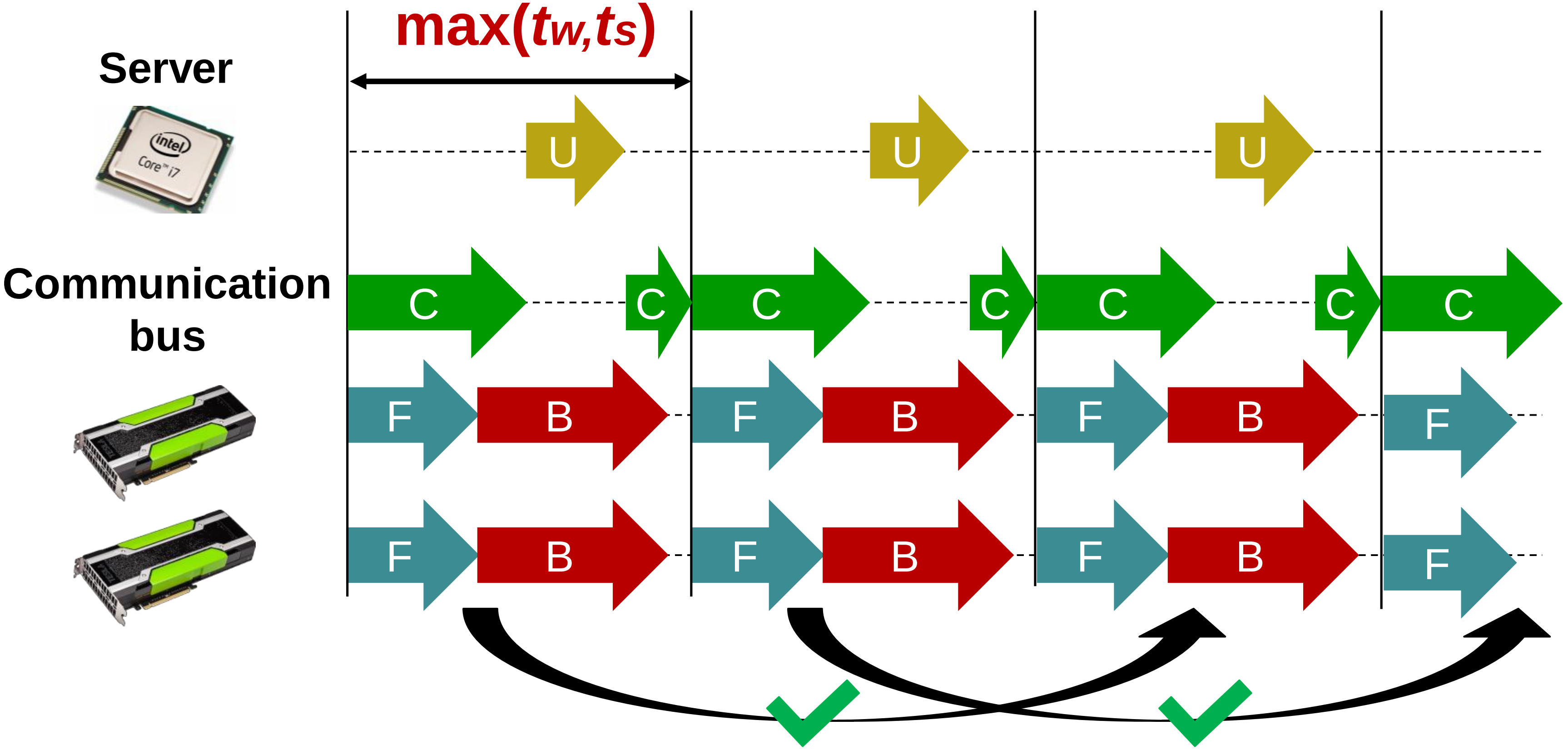
- **Proposed data parallel learning flow w/ two GPUs**



With proposed method, gradient calculation doesn't reflect the last batch update, and so we can overlap the parameter integration with the gradient calculation.

Proposed method

- **Proposed data parallel learning flow w/ two GPUs**



Gradient calculation reflects 2 steps earlier batch. The proposed method can eliminate the communication bottleneck.

- **However, it is not naïve SGD, and so we must verify the accuracy.**

Acceleration ratio

- **Conventional method takes ($t_w + t_s$) to process 1 iteration.**
- **Proposed method takes the longer one of t_w and t_s**

- **Compared to conventional data parallelism, the proposed method accelerates learning by r_{ws}.**

- **r_{ws} can be expressed as follows:**

$$r_{ws} = \frac{t_w + t_s}{max(t_w, t_s)}$$

$$t_w = \text{gradient calculation time}$$

$$t_s = \text{communication and update time}$$

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Experimental environment

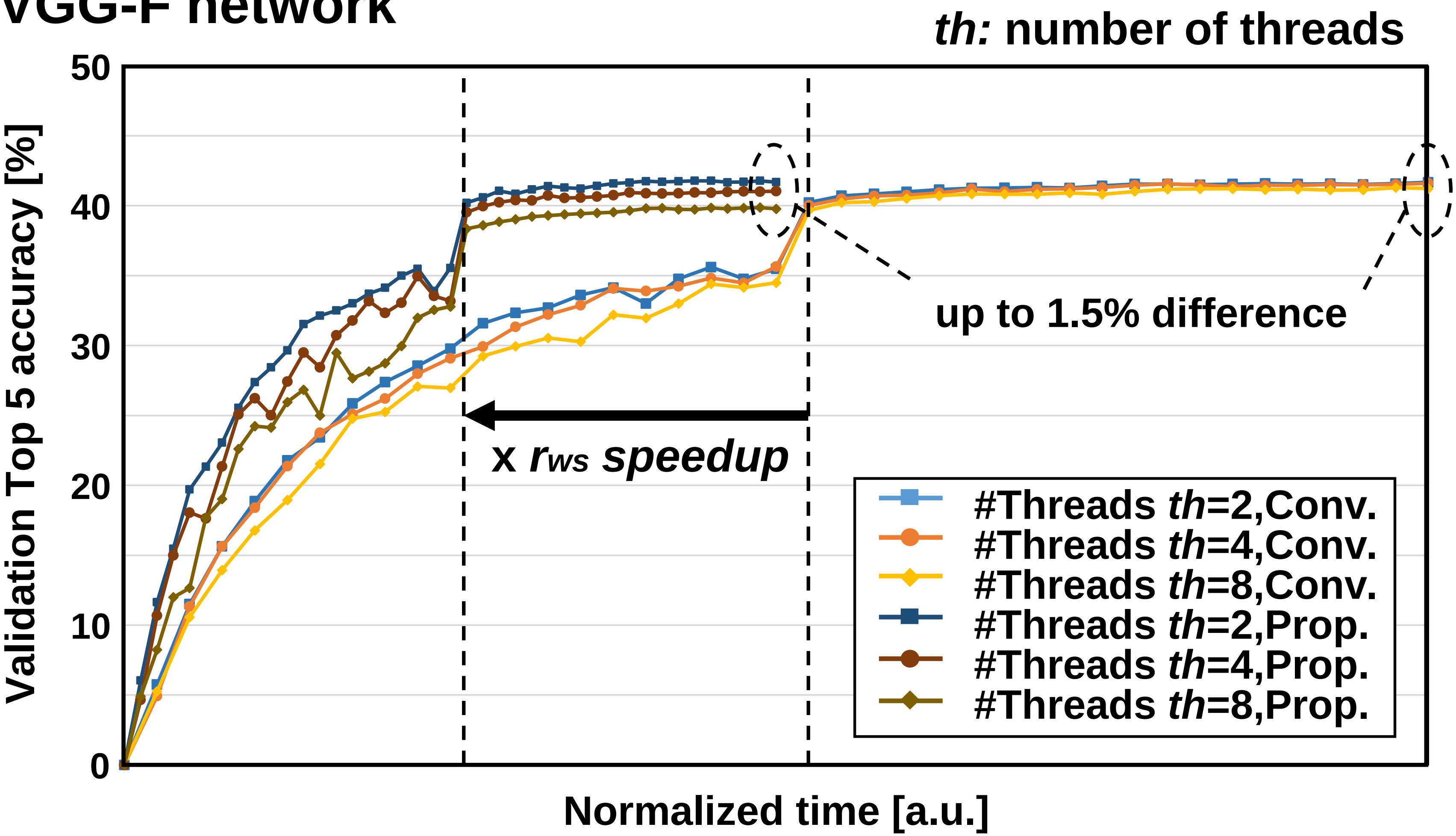
CPU	Core i7 6700K
GPU	Nvidia Geforce GTX 1080
Framework	Matconvnet
Communication interface (CPU-GPU)	PCI express Gen3 x16
Network	VGG-F network ResNet-50
Optimizer	MomentumSGD
Learning rate (based on linear scaling rule)	VGG-F: 0.001 * *th* ResNet: 0.025 * *th* (divided by 10 every 30 epoch)
Dataset	ImageNet-1k (50k images for train)

th: number of threads

A. Krizhevsky, "One weird trick for parallelizing convolutional neural network"

Training convergences evaluation

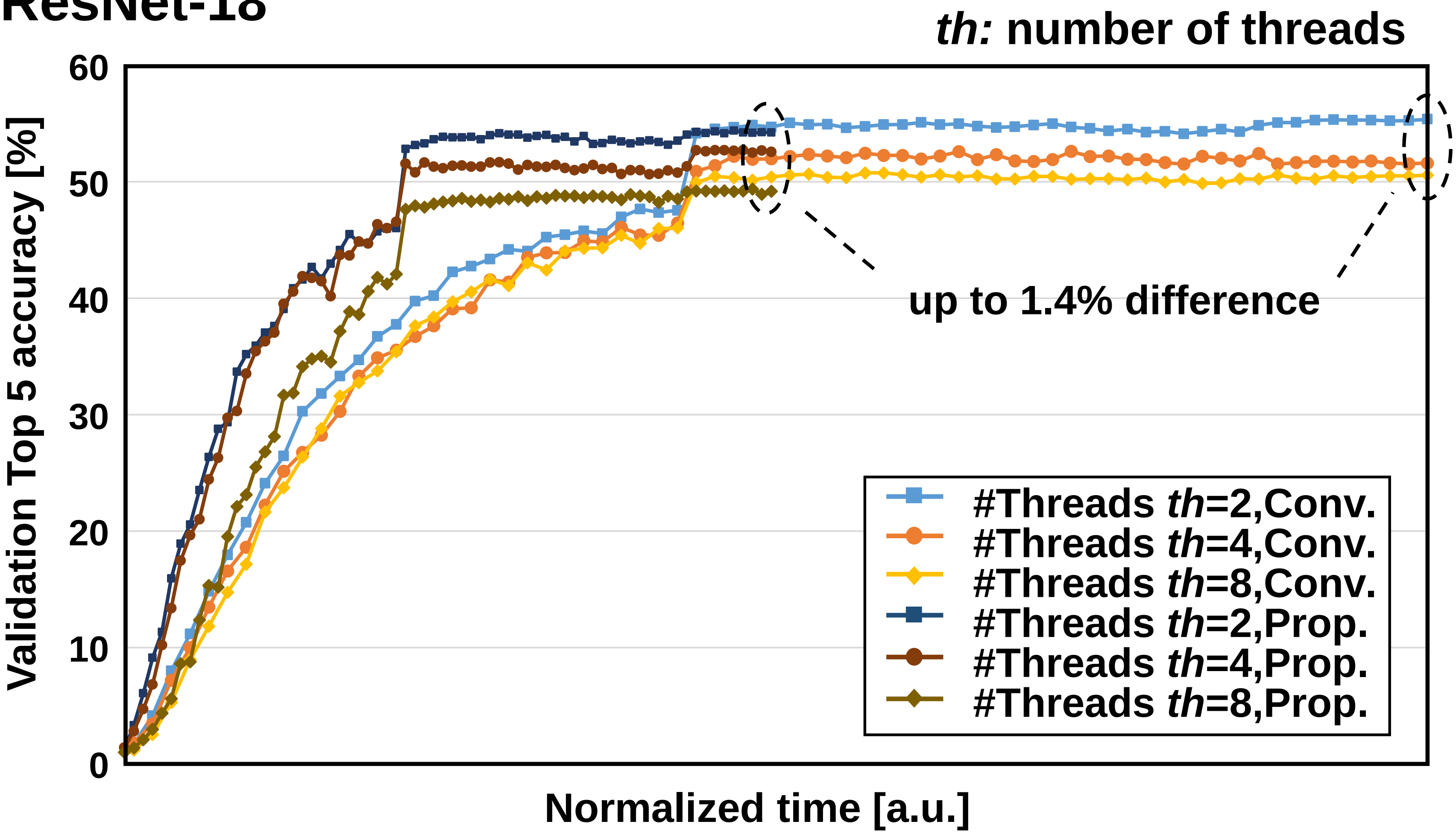
- VGG-F network



The final accuracy degradation is 1.5% at the maximum.There is a possibility that this accuracy degradation can be suppressed by changing optimizer or tuning parameters well.

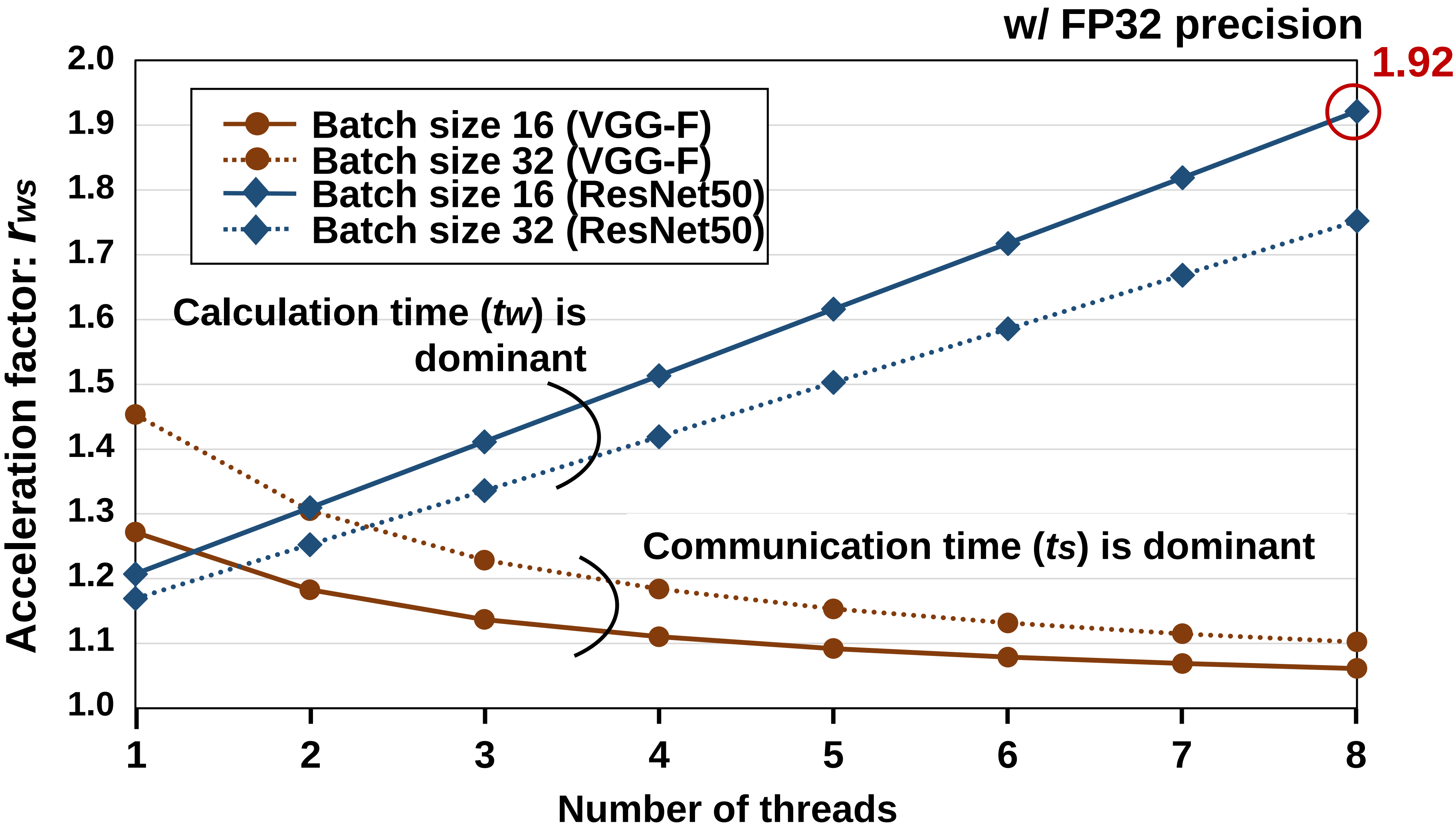
Training convergences evaluation

- **ResNet-18**



Resnet-18's result exhibits a similar tendency with VGG-f's result.
The final accuracy degradation is 1.4% at the maximum.

Acceleration ratio evaluation



We calculated the ratio *rws* by measuring communication and calculation time. In ResNet50, *rws* reaches 1.92 when the number of threads is eight and the batch size is 16.

Conclusion

- **In conventional data parallelism, when the gradient data size is large, communication latency can be bottleneck.**
- **Using one step delayed weights for gradient calculation is proposed.**
  - **Nevertheless proposed method is not naïve SGD, there is up to 1.5% difference between the accuracy of proposed method and that of conventional one.**
  - **We confirmed that the proposed method actually accelerates learning with general equipment.**
  - **Particularly in ResNet50, *rws* reaches 1.92 when the number of threads is eight and the batch size is 16.**