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Developing a Loss Prediction-based Asynchronous Stochastic Gradient Descent Algorithm for Distributed Training of Deep Neural Networks

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Contents

Introduction

- Deep Neural Network (DNN) has shown significant results in image processing [1].
- Increasing trends in Deep Learning:
    - Size of training datasets
    - Architecture complexity of the neural networks
- Limitations in computing infrastructures:
    - Central Processing Unit (CPU): less computing capacities
    - Graphics Processing Unit (GPU): restricted memory size
    - Tensor Processing Unit (TPU): limited generalization
- Distributed training DNNs is a promising strategy, because:
    - Computing in parallel
    - Utilizing abundant computing resources on demand

Introduction

- An example of the distributed training system

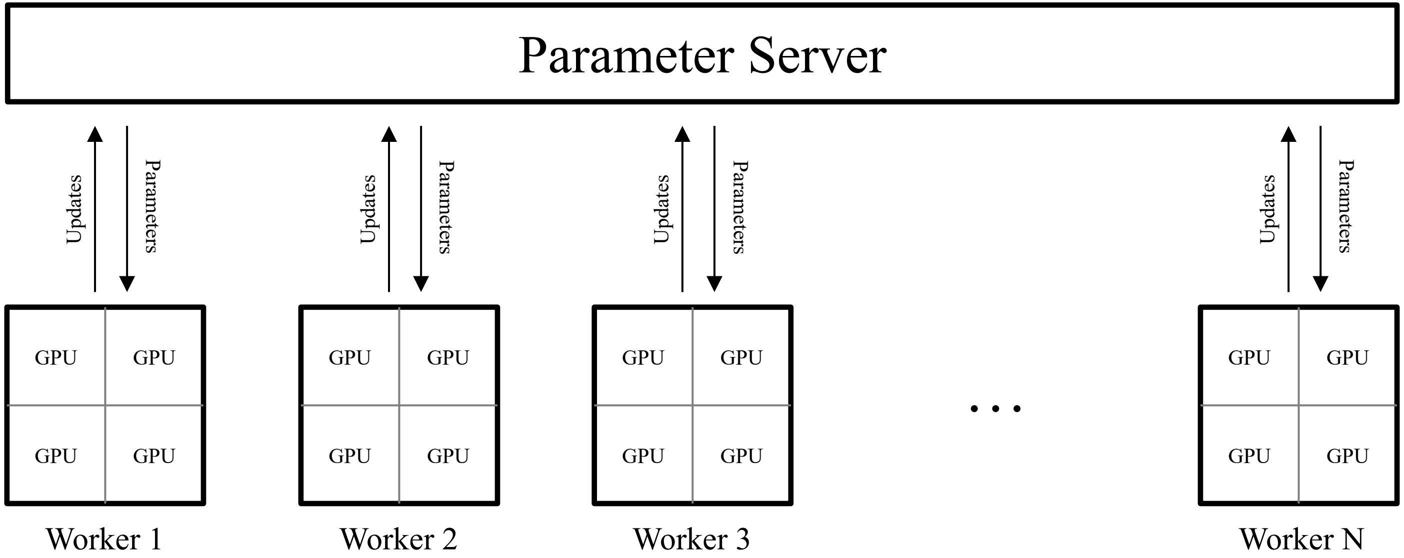


Figure 1. An example of distributed training system

Motivations

- SGD and popular SGD-based optimizers for distributed training:
  - SGD: $\omega_{t+1} = \omega_t - \gamma \cdot \nabla_{\omega_t} \ell(f_{\omega_t}(x_i), y_i)$ Single machine
  - SSGD: $\omega_{t+1} = \omega_t - \gamma \cdot \frac{1}{M} \cdot \sum_{j=1}^{M} (\frac{1}{b} \sum_{i=1}^{b} \nabla_{\omega_t} \ell(f_{\omega_t}(x_{i,j}), y_{i,j}))$ Synchronous barrier
  - ASGD [3,4]: $\omega_{t+\tau+1} = \omega_{t+\tau} - \gamma \cdot g \frac{1}{b} \sum_{i=1}^{b} \nabla_{\omega_t} \ell(f_{\omega_t}(x_i), y_i)$ Delayed update
  - DC-ASGD [5]: $\omega_{t+\tau+1} = \omega_{t+\tau} - \gamma \cdot (g_m + \lambda_t g_m \otimes g_m \otimes (w_t - w_{bak}(m)))$ Remarkable work solving the delay issue in ASGD

Motivations

- The delay issue in ASGD

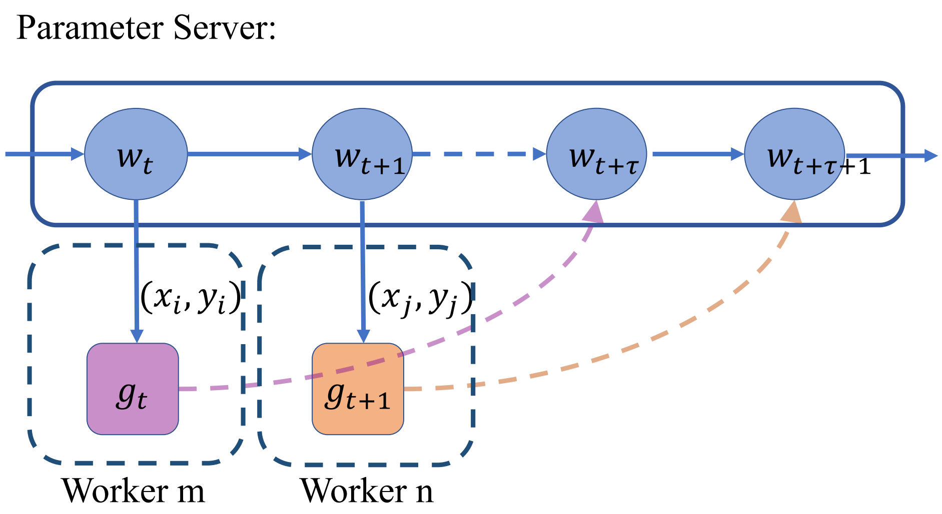


Figure 2. ASGD weight updating procedure

Motivations

- Performance of DC-ASGD with different numbers of workers

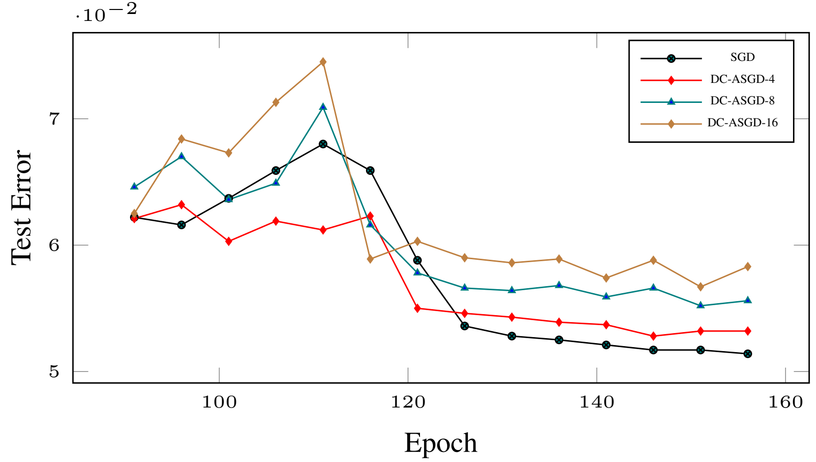


Figure 3. Performance of DC-ASGD training ResNet-18 on CIFAR-10 w.r.t. number of workers

Distributed training with loss compensation

- We propose LC-ASGD to address the delayed updating problem in ASGD.
- The trend of loss values during training is modelled as a time series by a **loss predictor**.
- We use a **step predictor** to model delayed steps for the loss predictor.
- We extend regular **batch normalization** to an **asynchronous** version to further improve the performance.

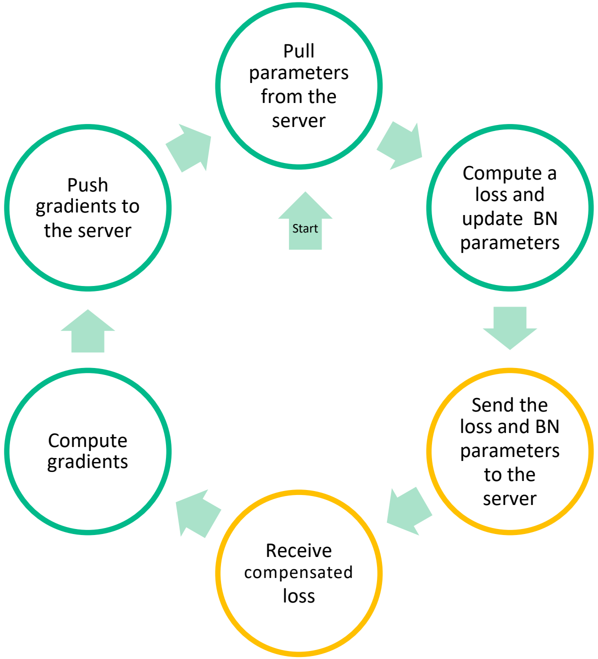
Distributed training with loss compensation

- Training processes of each worker

Algorithm 1 The computations performed by a worker, m

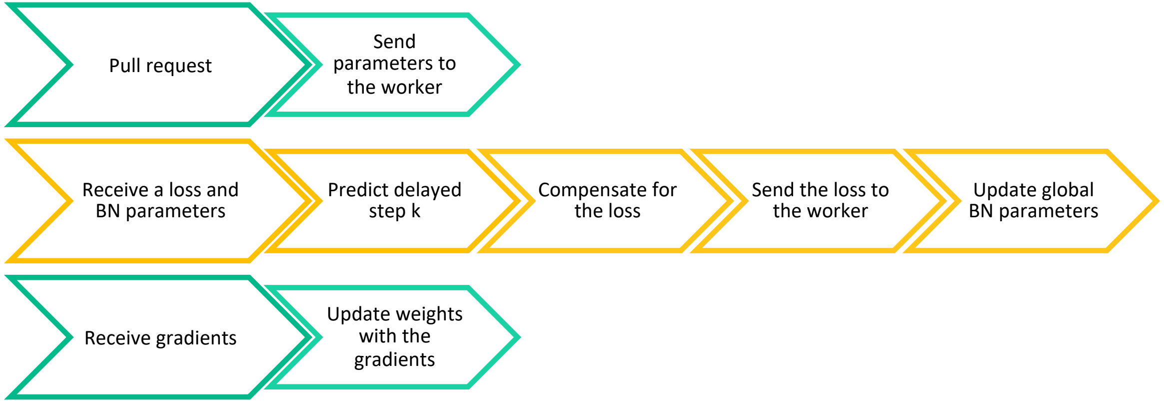
Initialize:
$state_m = \{loss : 0, mean : \{\ \}, var : \{\ \}, t_{comm} : 0, t_{comp} : 0\}$,
$z \in \{1, 2, ..., Z\}$, t_0, t_1

Pull w_t from the parameter server at timestamp t_0
Receive the weights w_t at timestamp t_1
Record the pulling time cost $state_m[t_{comm}] = t_1 - t_0$
Compute loss $\ell_m = \ell(f_{w_t}(x_i),\ y_i)$
Record the local loss $state_m[loss] = \ell_m$
Store mean μ_z in each BN layer bn_z into $state_m[mean]$
Store variance σ_z in each BN layer bn_z into $state_m[var]$
Push all recordings $state_m$ to the parameter server
Receive loss compensation ℓ_{delay} from the parameter server at timestamp t_2
Compute gradient $g_m = \nabla_{w_t}(\ell_m + \lambda \cdot \ell_{delay})$, finishing at timestamp t_3
Record computational time cost $state_m[t_{comp}] = t_3$ - t_2
Push the gradients g_m to the parameter server



Distributed training with loss compensation

- Training processes of the parameter server



Algorithm 2 LC-ASGD: parameter server

Input: learning rate γ

Initialize: $t = 0$, $E_{bn_z} = 0$, $Var_{bn_z} = 1$, w_0 is initialized randomly, $iter = [\ ]$, $m \in \{1, 2, ..., M\}$, $z \in \{1, 2, ..., Z\}$

repeat

- **if** receive $state_m$ **then**
  - Append m to $iter$
  - Predict step $k_m = stepPredictor(m, state_m[t_{comm}, state_m[t_{comp}],\ iter)$
  - Predict loss ℓ_{delay} for the next k_m steps by $lossPred(state_m[loss], k)$
  - Send ℓ_{delay} to worker m
  - Update $E_z = (1 - d) * E_z + d * state_m[mean_z]$
  - Update $Var_z = (1 - d) * Var_z + d * state_m[var_z]$
- **else if** receive g_m **then**
  - $w_{t+1} = w_t - \gamma \cdot g_m$
  - $t = t + 1$
- **else if** receive pull request from worker m **then**
  - Send w_t to worker m
- **end if**

until *forever*

Distributed training with loss compensation

- Loss predictor

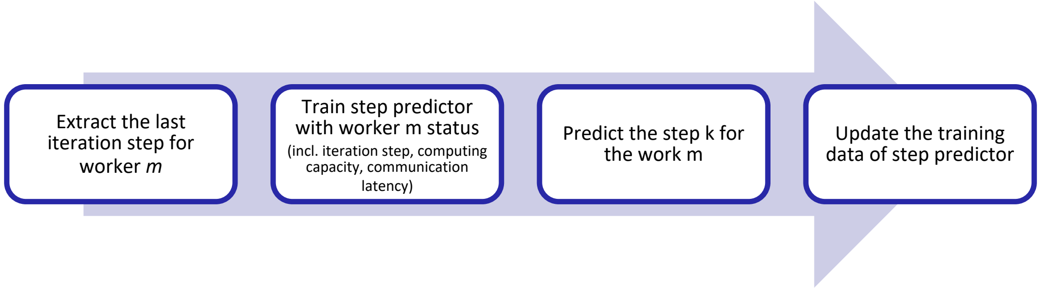
Algorithm 3 LC-ASGD: loss predictor

Input: loss ℓ_m (the loss received from worker m), step k_m
Initialize: ℓ_t (the latest loss of the network)

Train *lossPred* with $(data = \ell_t,\ label = \ell_m)$
$predictions = lossPred(data = \ell_m,\ future = k)$
$\ell_{delay} = sum(predictions)$
$\ell_t = \ell_m$

Return: ℓ_{delay}

- Step predictor



Algorithm 4 LC-ASGD: step predictor

Input: worker rank m, t_{comm}, t_{comp}, iteration recording *iter*
Initialize: $step_m = 0$, t^m_{comm}, t^m_{comp}, $m \in \{1, 2, \ldots, M\}$

Extract the last iteration $step_t$ of worker m from *iter*
Train *stepPred* with
$(data = \{step_m, t^m_{comm}, t^m_{comp}\},\ label = step_t)$
$k_m = stepPred(data = \{step_t, t_{comm}, t_{comp}\},\ future = 1)$
$t^m_{comm}, t^m_{comp}, step_m = t_{comm}, t_{comp}, step_t$

Return: k_m

Experiments

- ✓ We evaluated the proposed LC-ASGD on CIFAR-10 and ImageNet benchmark datasets.
- ✓ The experiments were carried out on a GPU cluster equipped with NVIDIA Tesla V100 GPUs.
- ✓ The hyper-parameters followed the settings in the original works [5,6].
- ✓ The results demonstrate that LC-ASGD delivers significant results outperforming other distributed training algorithms.

Experiments

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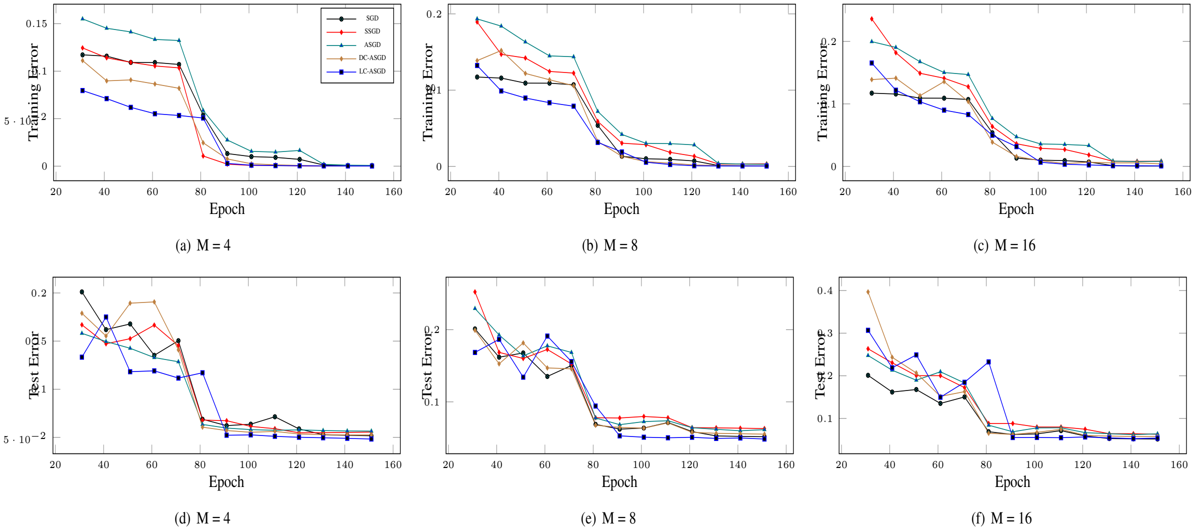
- Learning curves of ResNet-18 with Async-BN on CIFAR-10 dataset



(a) M = 4 (b) M = 8 (c) M = 16

(d) M = 4 (e) M = 8 (f) M = 16

Figure 4. Error rates of the global model ResNet-18 with Async-BN as the training progresses on CIFAR-10

Experiments

- Evaluation results of ResNet-18 on CIFAR-10 dataset

Table 3. Training performance of ResNet-18 on CIFAR-10.

# Workers	Algorithm	CIFAR-10 BN		CIFAR-10 Async-BN	
		Test Error (%)	Perf. Deg. (%)	Test Error (%)	Perf. Deg. (%)
1	SGD	5.15	Baseline	5.15	Baseline
4	SSGD	5.67	10.10	5.57	8.16
	ASGD	5.73	11.26	5.65	9.71
	DC-ASGD	5.33	3.50	5.22	1.36
	LC-ASGD	**4.98**	**-3.3**	**4.87**	**-5.44**
8	SSGD	6.19	20.19	6.01	16.70
	ASGD	6.38	23.88	6.27	21.75
	DC-ASGD	5.72	11.07	5.58	8.35
	LC-ASGD	**5.11**	**-0.78**	**4.96**	**-3.69**
16	SSGD	6.41	24.47	6.20	20.39
	ASGD	6.59	27.96	6.41	24.47
	DC-ASGD	6.05	17.48	5.83	13.20
	LC-ASGD	**5.76**	**11.84**	**5.52**	**7.18**

Experiments

- Learning curves of ResNet-50 with Async-BN on ImageNet dataset

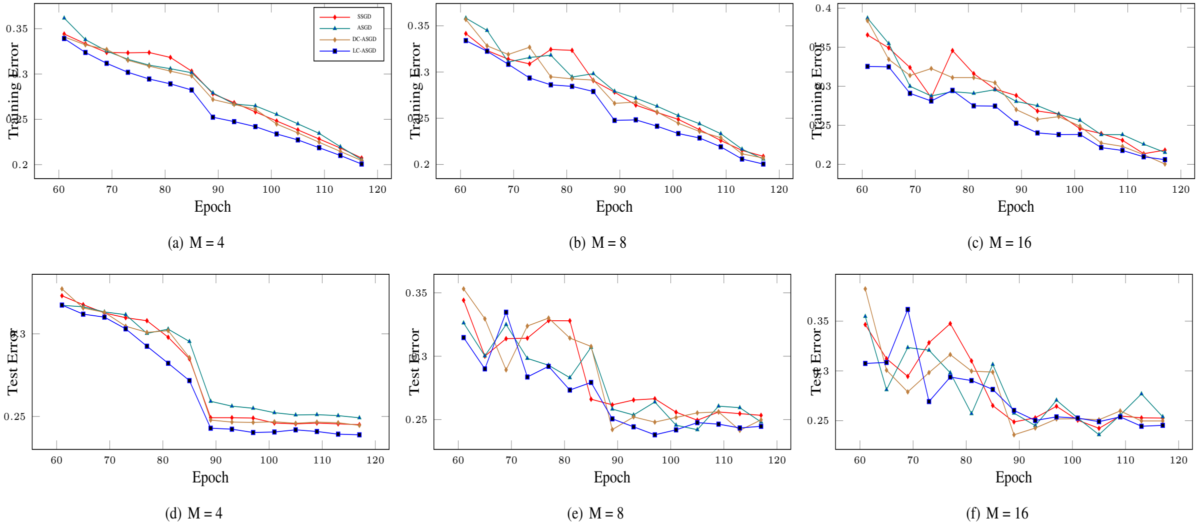


Figure 5. Error rates of the global model ResNet-50 with Async-BN as the training progresses on ImageNet

Experiments

- Evaluation results of ResNet-50 on ImageNet dataset

Table 4. Training performance of ResNet-50 on ImageNet.

# Workers	Algorithm	ImageNet BN		ImageNet Async-BN	
		Test Error (%)	Perf. Deg. (%)	Test Error (%)	Perf. Deg. (%)
4	SSGD	24.61	Baseline	24.49	Baseline
	ASGD	24.99	1.54	24.90	1.67
	DC-ASGD	24.53	-0.33	24.46	-0.12
	LC-ASGD	**23.91**	**-2.84**	**23.86**	**-2.57**
8	SSGD	25.24	2.56	25.11	2.53
	ASGD	25.71	4.47	25.64	4.70
	DC-ASGD	25.98	5.57	24.89	1.63
	LC-ASGD	**24.17**	**-1.79**	**24.07**	**-1.71**
16	SSGD	25.80	4.84	25.62	4.61
	ASGD	25.96	5.49	25.81	5.39
	DC-ASGD	25.41	3.25	25.23	3.02
	LC-ASGD	**24.99**	**1.54**	**24.82**	**1.35**

Experiments

- Performance of the loss predictor and the step predictor

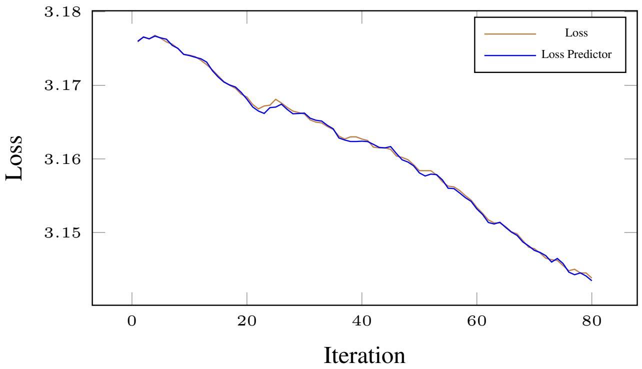


Figure 6. Performance of the loss predictor for ResNet-50 w.r.t. number of iterations on ImageNet training with 16 workers

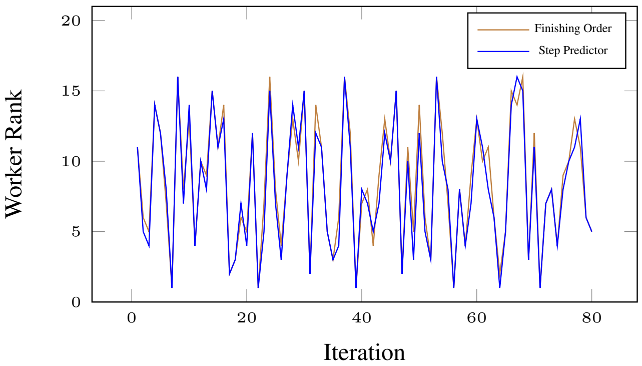


Figure 7. Performance of the step predictor for ResNet-50 w.r.t. number of iterations on ImageNet training with 16 workers

Experiments

- Overhead analysis of training on CIFAR-10 and ImageNet

Table 5. Average time of a training iteration on CIFAR-10.

# Workers	4	8	16
Loss Pred. (ms)	1.28	1.29	1.30
Step Pred. (ms)	1.37	1.43	1.48
Total Training (ms)	32.23	32.84	34.64
Overhead (%)	8.22	8.28	8.03

Table 6. Average time of a training iteration on ImageNet.

# Workers	4	8	16
Loss Pred. (ms)	1.27	1.29	1.33
Step Pred. (ms)	1.36	1.45	1.50
Total Training (ms)	183.23	185.68	188.71
Overhead (%)	1.44	1.48	1.50

Conclusion

- In this work, we discussed:
  - The issue of synchronization barrier in SSGD
  - The delayed gradient updating in ASGD
  - The limitation of DC-ASGD
- We proposed a novel distributed training algorithm with following components:
  - Workers
  - Parameter server with asynchronous batch normalization
  - Loss predictor
  - Step predictor
- Experiment results show that our LC-ASGD delivers outstanding accuracy compared with other algorithms.

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Thank you!