WeightGrad: Geo-Distributed Data Analysis Using Quantization for Faster Convergence and Better Accuracy

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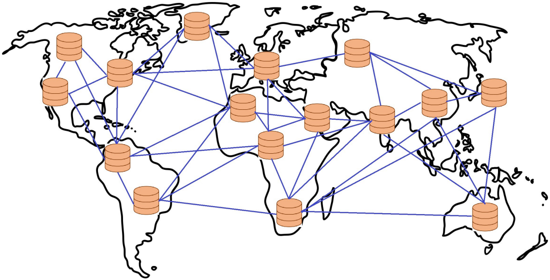
Problem Overview



- Large scale cloud organizations are establishing data centers and "edge" clusters globally to provide their users low latency access to their services.

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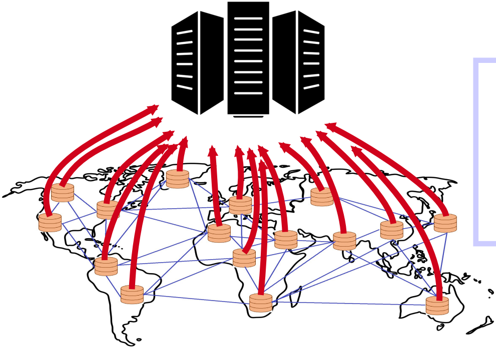
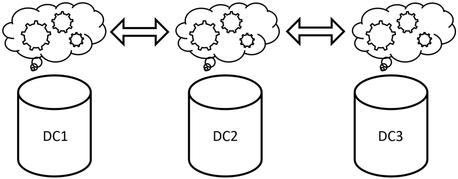


Problem

- Powerful machines.
- Huge memory.
- Large amount of time.

Problem Overview

Clearly, **centralization** is not a feasible solution which motivates the need to **distribute the DNN** system across multiple data centers.



Problem Definition

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- How to ensure faster convergence without loss of accuracy

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- adapts both **weight and gradient quantization** to provide best speedup possible on WAN
- proposes a **synchronous structure** to prevent the loss in accuracy due to quantization

WeightGrad System

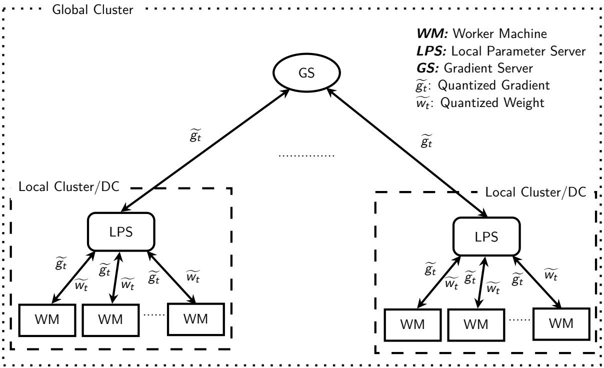
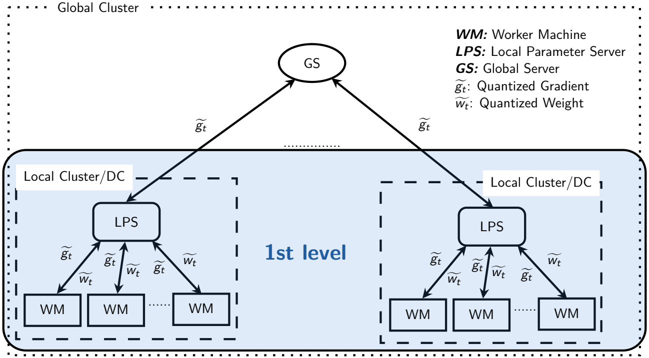


Figure: WeightGrad Tree Structure

Two Level Structure



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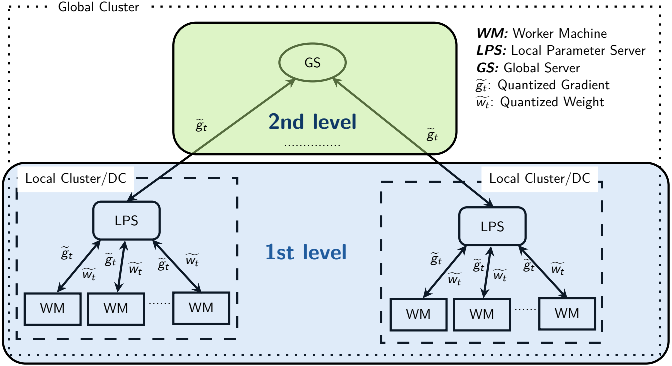

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Local Cluster

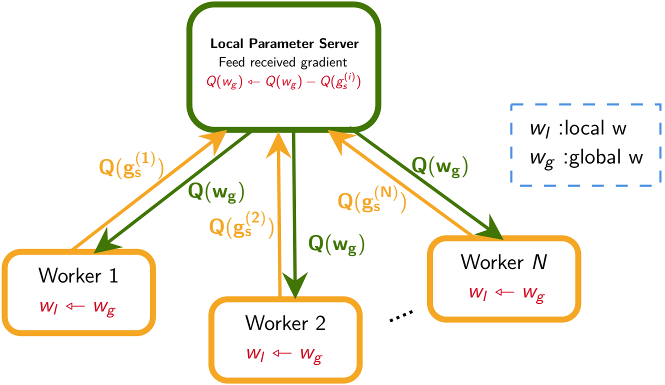
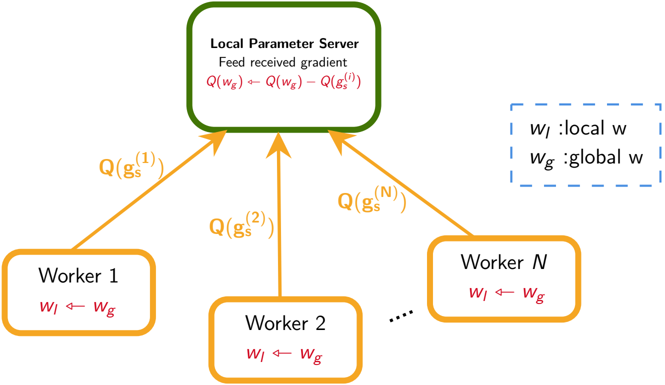


Figure: WeightGrad: Local Cluster

Local Cluster



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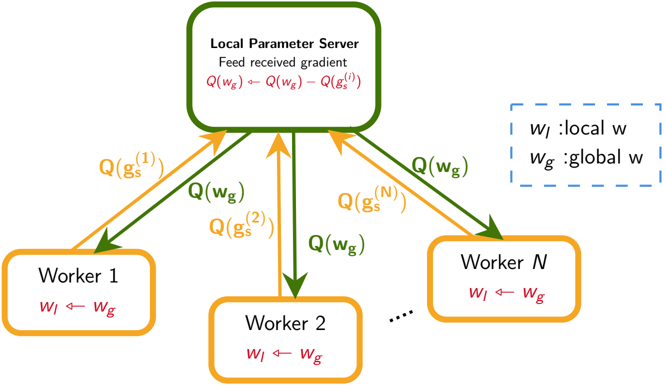

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LPS with Gradient Synchronizer

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Dynamic Threshold

- Gradient Synchronizer maintains a dynamic threshold for distributing the gradient updates.

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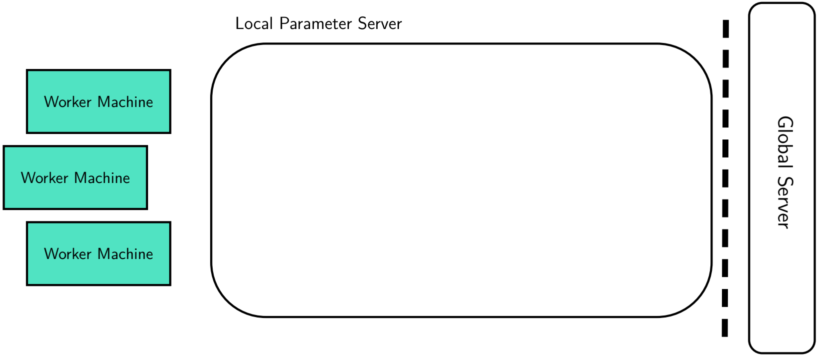
Fixed Interval

- To synchronize the communication process, Gradient Synchronizer maintains a fixed interval T, within which it receives aggregated gradient values from the GS.
- If an LPS does not get update from the GS within T, it stops sending updates to the WMs until gradient updates are received from the GS.

LPS with Gradient Synchronizer



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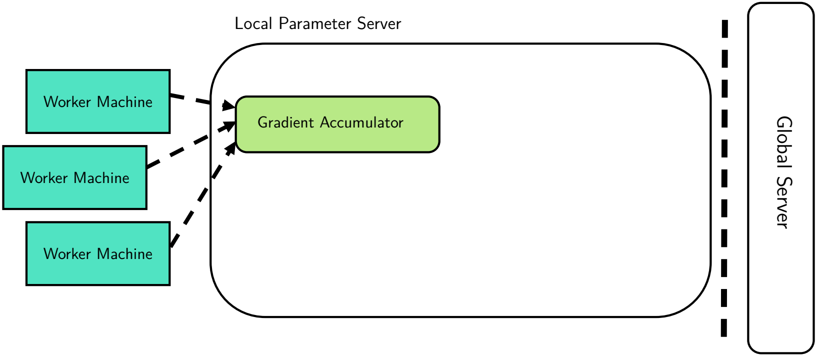
LPS with Gradient Synchronizer



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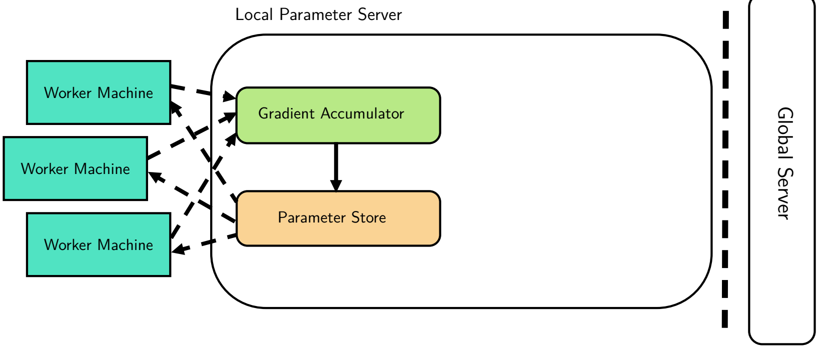

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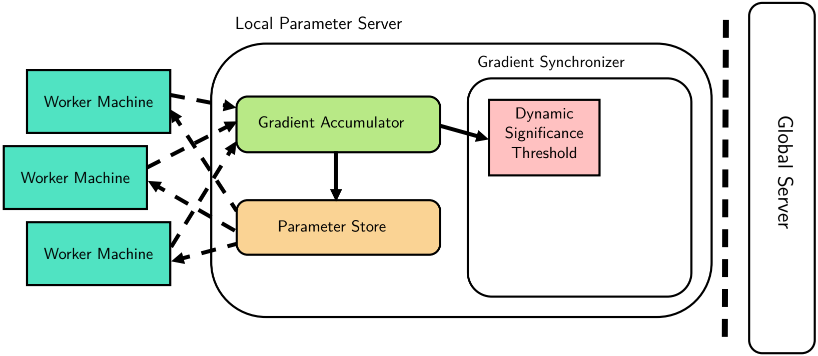

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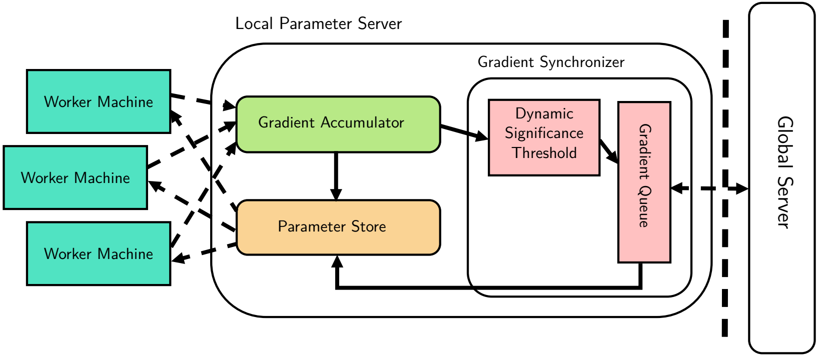

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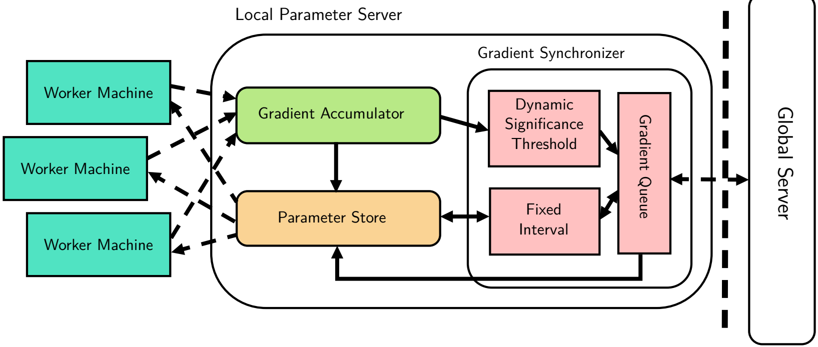

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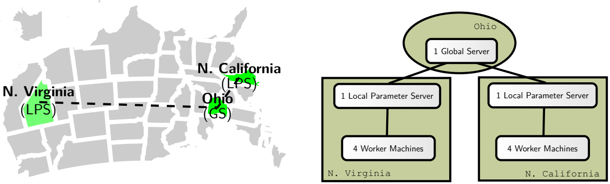
Amazon EC-2

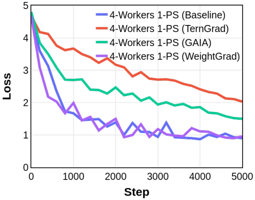


(a) (b)

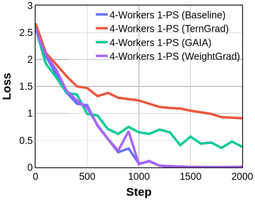
Figure: (a)Deployment Regions in AWS(b)Instance Hierarchy

Instances	Instance Type	RAM	vCPU	GPU	B/W
11	g3s.xlarge, 64-bit Ubuntu Server 16.04 LTS	30.5 GiB	4	NVIDIA Tesla M60 GPU	10 Gbps

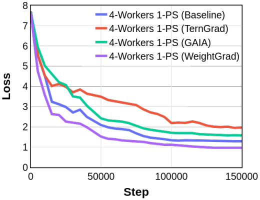
Training Loss Analysis



(a) Training Loss for CifarNet



(b) Training Loss for VGGNet



(c) Training Loss for ImageNet

Figure: (a) Training loss for CifarNet model on CIFAR-10 dataset, (b) Training loss for VGGNet model on CIFAR-10 dataset, (c) Training loss for AlexNet on ImageNet dataset

SpeedUp Analysis

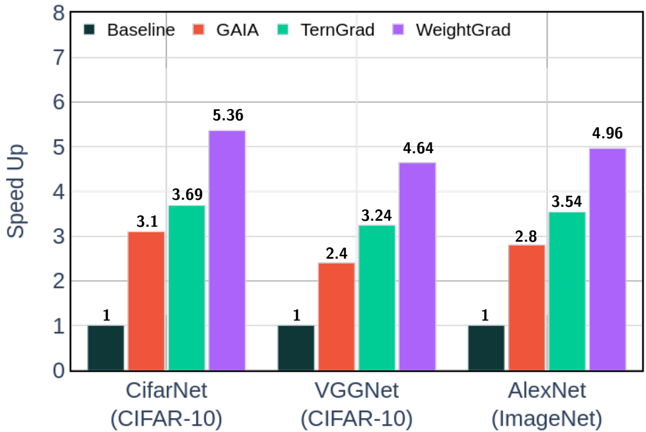


Figure: Training Speed Comparison

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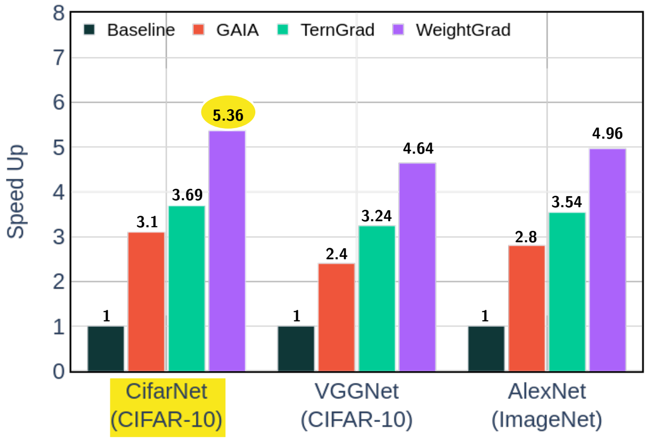

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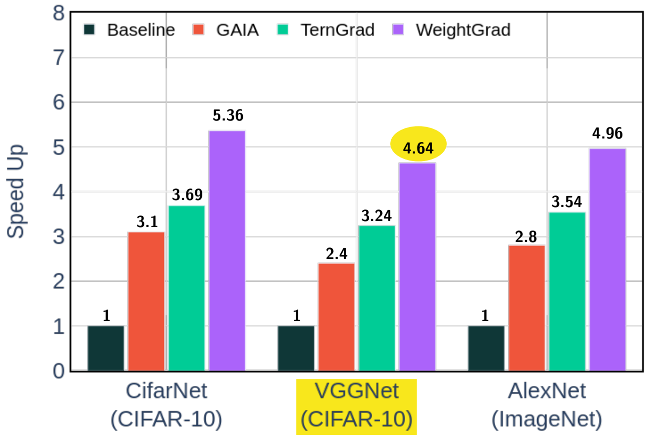

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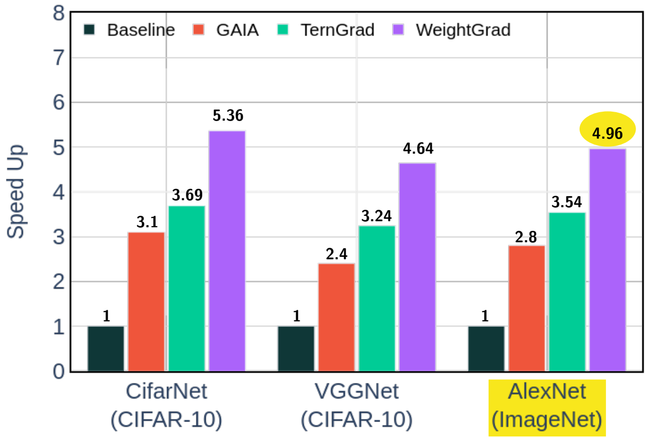

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Accuracy Comparison: CIFAR-10

Model	SGD	Base LR	Total mini-batch size	Steps	Gradients	Workers	Accuracy
CifarNet	GD	0.1	128	50k	Baseline	4	84.56%
					Gaia	4	83.48%(-1.08%)
					TernGrad	4	82.41%(-2.15%)
					WeightGrad	**4**	**84.56%(-0.00%)**
	GD	0.1	512	50k	Baseline	8	83.19%
					Gaia	8	83.04%(-0.13%)
					TernGrad	8	81.40%(-1.79%)
					WeightGrad	**8**	**83.21%(+0.03%)**
VGG-Net	GD	0.1	512	50k	Baseline	8	88.14%
					Gaia	8	87.19%(-0.95%)
					TernGrad	8	86.3%(-1.84%)
					WeightGrad	**8**	**88.13%(-0.01%)**

Table: Result of WeightGrad on CIFAR-10 dataset

Accuracy Comparison: ImageNet

Model	Steps	Training Method	Top-1 Accuracy	Top-5 Accuracy
AlexNet	185k	Baseline	58.17%	80.19%
		Gaia	58.02%(-0.15%)	80.20%(+0.01%)
		TernGrad	57.32%(-0.85%)	80.18%(-0.01%)
		Deep Gradient Compression	58.20%(+0.03%)	80.20%(+0.01%)
		WeightGrad	**59.28%(+1.06%)**	**80.25%(+0.06)**

Table: Comparison of training methods on ImageNet data

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- **Results:** WeightGrad achieves,
  - **2.4-5.36× speedup** over state-of-the-art distributed systems
  - **0.03-1.06% accuracy gain** over Baseline

THANK YOU!

Syeda Nahida Akter and Muhammad Abdullah Adnan, "WeightGrad: Geo-Distributed Data Analysis Using Quantization for Faster Convergence and Better Accuracy," Proc. of ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (ACM SIGKDD 2020), San Diego, CA, USA, August 23-27, 2020.