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

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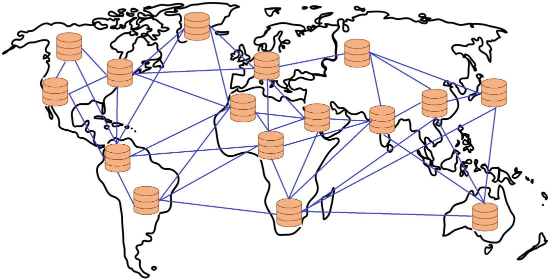
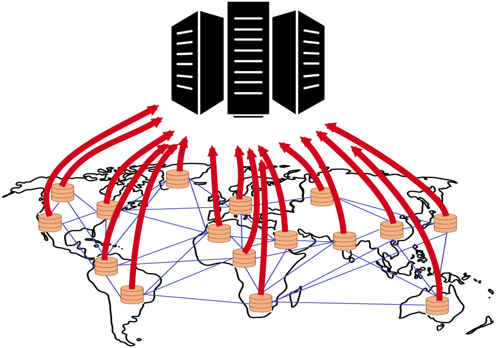
Problem Overview



- Large scale cloud organizations are establishing data centers and "edge" clusters globally to provide their users low latency access to their services.
- Microsoft and Google have tens of data centers, with the latter also operating 1500 edges worldwide.

Problem Overview



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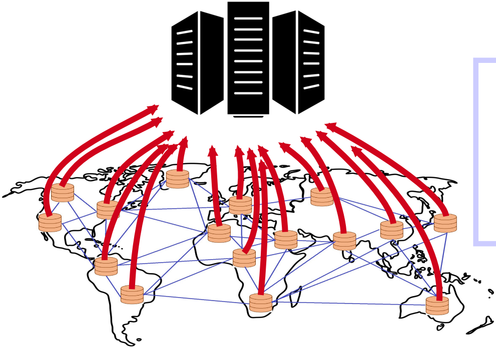
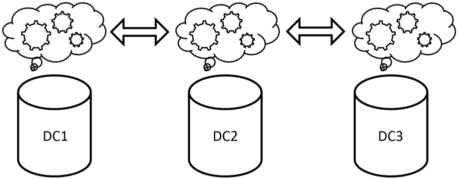


Problem

- 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.



Motivation

- There are many large-scale distributed ML systems, among them, the **parameter server architecture** provides a performance advantage over other systems for many ML applications and has been widely adopted in many ML systems.

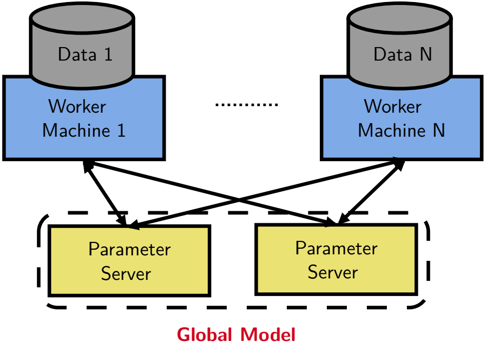


Figure: Basic PS architecture

Motivation

- Deployment of PS architecture on WANs needs to synchronize updates among the workers which is a high cost operation that can significantly slow down the worker machines.

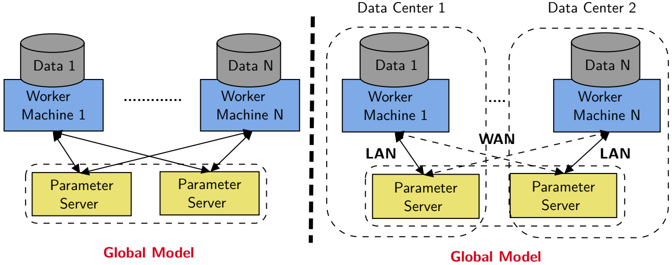


Figure: Deploy PS on WANs

Motivation

- Introduction of quantization has provided significant speedup in convergence in deep learning training.

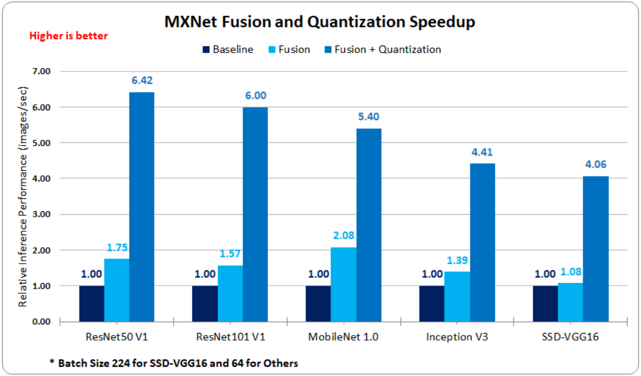


Figure: MXNet speedup graph [Chen et al. (2015)]

Motivation

- But quantizing parameters for faster communication between worker and parameter server also causes loss in precision thus some loss in accuracy. Here is an accuracy table from [Hou et al. (2019)].

Table 3: Top-1 and top-5 accuracies (%) on ImageNet.

weight	gradient	$N=2$		$N=4$		$N=8$	
		top-1	top-5	top-1	top-5	top-1	top-5
FP	FP	55.08	78.33	55.45	78.57	55.40	78.69
LAQ4	FP	53.79	77.21	54.22	77.53	54.73	78.12
	SQ3 (no clipping)	52.48	75.97	52.87	76.40	53.18	76.62
	SQ3 (clip, $c=3$)	54.13	77.27	54.23	77.55	54.34	78.07

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- How to efficiently utilize limited WAN b/w
- How to ensure faster convergence without loss of accuracy

Distributed ML Systems

- As a distributed ML system, the state-of-the-art method is : **"Gaia: Geo-Distributed MachineLearning Approaching LAN Speeds.", Kevin Hsieh, Aaron Harlap, Nandita Vijaykumar, Dimitris Konomis, Gregory R.Ganger, Phillip B. Gibbons, and Onur Mutlu. 2017.** [Hsieh et al. (2017)]

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- The goal of Gaia is to develop a geo-distributed ML system that
  - **minimizes communication over WANs**, so that the system is not bottle-necked by the scarce WAN bandwidth and
  - is **general** enough to be applicable to a wide variety of ML algorithms, without requiring any changes to the algorithms themselves.

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  - **minimizes communication over WANs**, so that the system is not bottle-necked by the scarce WAN bandwidth and
  - is **general** enough to be applicable to a wide variety of ML algorithms, without requiring any changes to the algorithms themselves.
- To address the key challenges in designing a general and effective ML system, Gaia proposes a new model called **Approximate Synchronous Parallel (ASP)**.

Basic Significance Filter

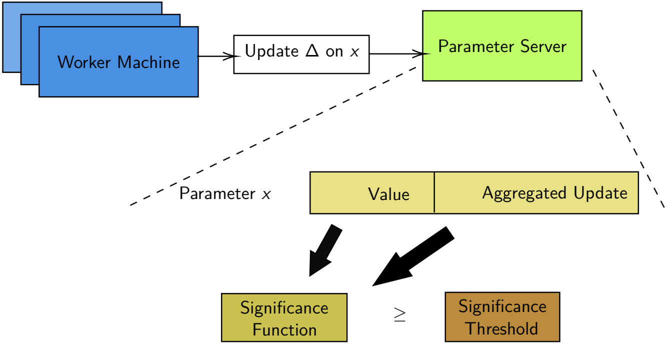

Figure: The Significance Filter [Hsieh et al. (2017)]

Gaia System

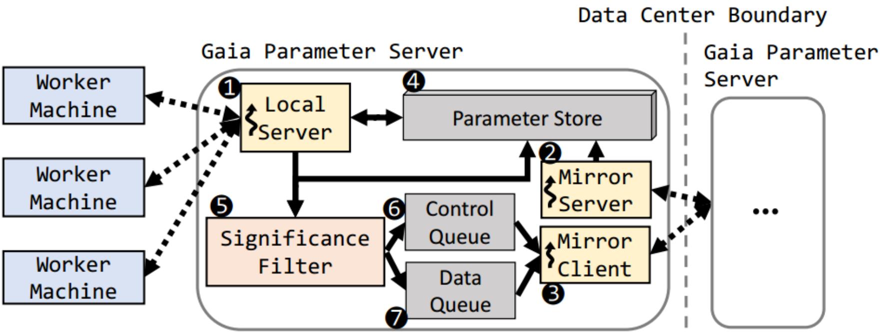

Figure: Key Component of Gaia [Hsieh et al. (2017)]

Problems of Gaia

- Exchanges parameters (weights and biases) with **full-precision**.

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- Exchanges parameters (weights and biases) with **full-precision**.
- Reducing communication using threshold value creates **inconsistency** among the data centers.
- Choosing **asynchronous structure** for communication over WAN can deteriorate the situation resulting in **divergence** of the model.

Gradient Sparsification

Key Ideas [Strom (2015)]

- Only send gradient larger than a predefined constant (Threshold quantization)
- Thus reduce the volume of data sent

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Disadvantages

- Maintaining the best possible threshold needs large amounts of experiments and largely varies from model to model, from dataset to dataset

Gradient Sparsification

Key Ideas [Dryden et al. (2016)]

- Own adaptive algorithm which uses a fixed proportion π and sends both positive and negative gradient updates maintaining that proportion

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Disadvantages

- Poor performance on deep learning models for using full precision parameters

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- Loss in accuracy due to compression

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Key Ideas [Seide et al. (2014)]

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Disadvantages

- Floating point scalar per column is required, cannot yield speed benefit on CNN
- "Cold Start" method requires first 24h of data processed without parallelism or quantization
- Significant reduction in accuracy if correct conditions are not maintained

Parameters and Gradient Quantization

- Paper: **"TernGrad: Ternary Gradients to Reduce Communication in Distributed Deep Learning"** [Wen et al. (2017)].

Key Ideas

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Disadvantages

- Poor performance in distributed setup
- Sacrificed upto 1.22% loss in top-1 accuracy for ImageNet dataset due to quantization
- Does not provide any synchronization model across multiple data centers

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- For distributed setup, **scarce of WAN bandwidth** can significantly slowdown the **convergence** of the Deep neural networks.
- DNN models hold **billions of parameters** and exchanging them in full precision (**hundreds to thousands mega bytes of data**) among the data centers in each epoch can dismiss the benefit of distributed setup.

Maintaining accuracy and convergence

- Though **quantization** has perceived **significant speedup**, quantizing gradients
  - slows convergence by a factor related to the **gradient quantization resolution and dimension** which contributes to fall in accuracy.

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From Challenge 1

- We need a model which not only **reduces communication time and bandwidth usage efficiently**, but also provides **a proper architecture to ensure convergence**.

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- We need a model which not only **reduces communication time and bandwidth usage efficiently**, but also provides **a proper architecture to ensure convergence**.

From Challenge 2

- We need to design a structure that utilizes the **speedup** achieved from the quantization and guarantees **same accuracy as the full precision** model.

Methodology

We propose **WeightGrad** that

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We propose **WeightGrad** that

- 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

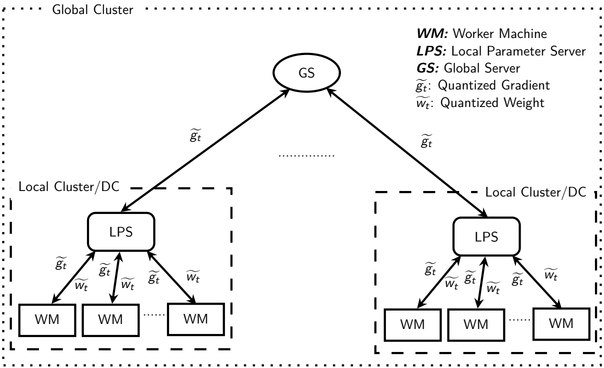
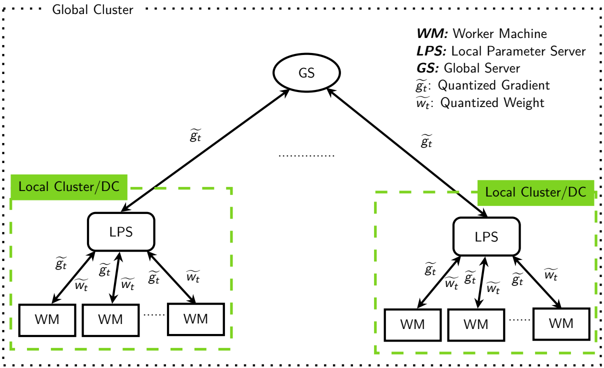


Figure: WeightGrad Tree Structure

WeightGrad System



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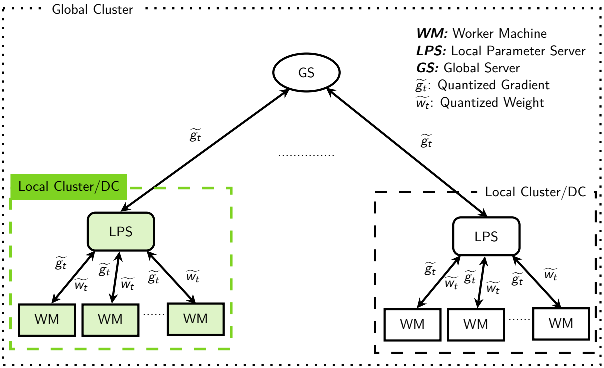

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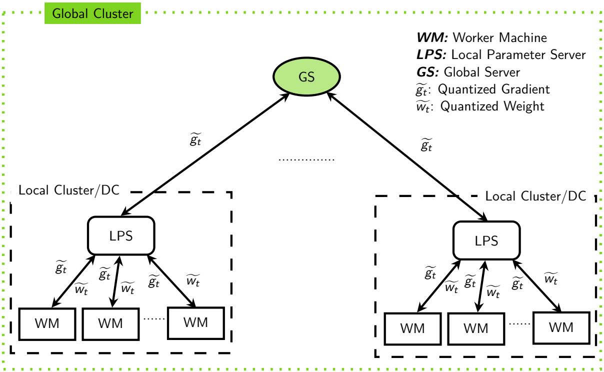

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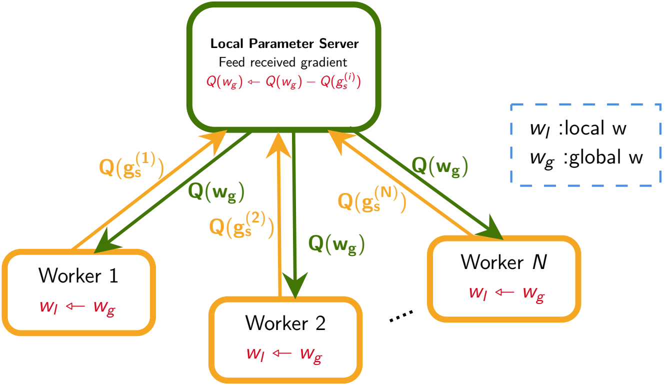

Figure: WeightGrad: Local Cluster

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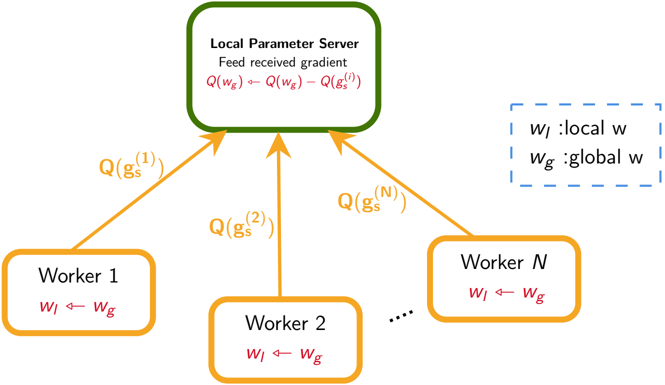

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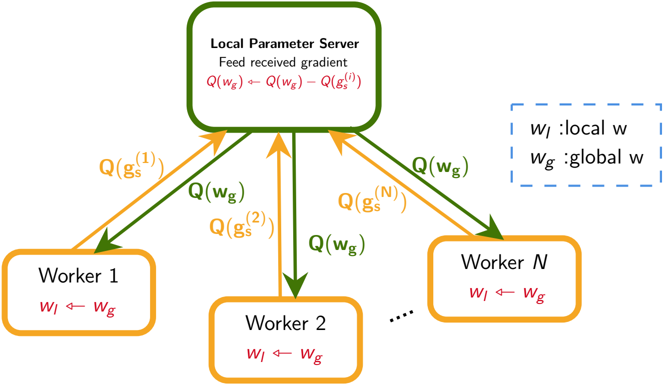

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LPS with Gradient Synchronizer

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Dynamic Threshold

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

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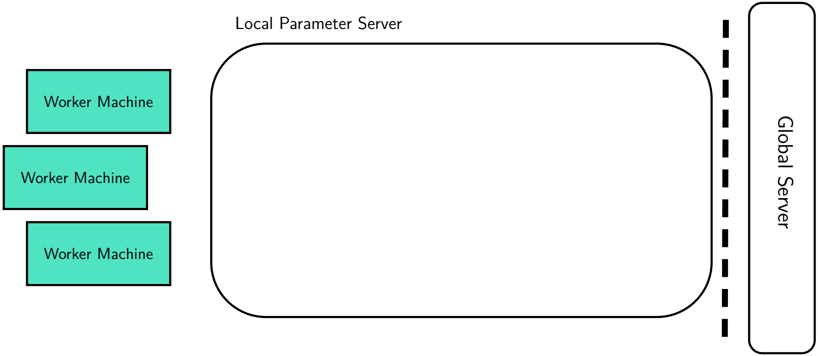
Fixed Interval

- 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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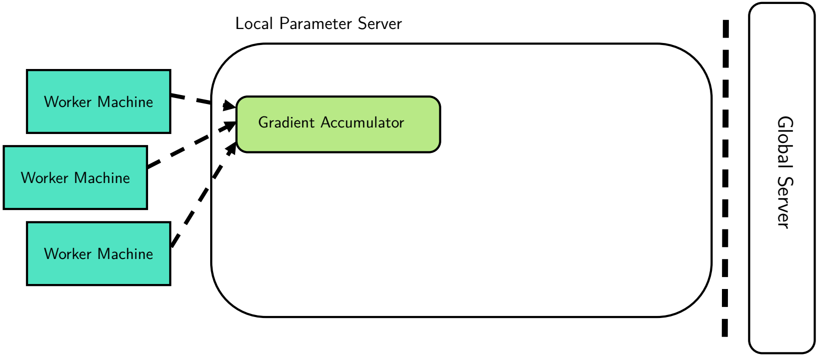

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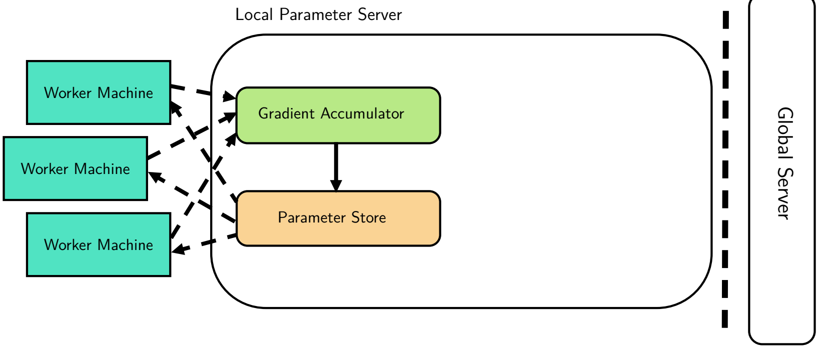

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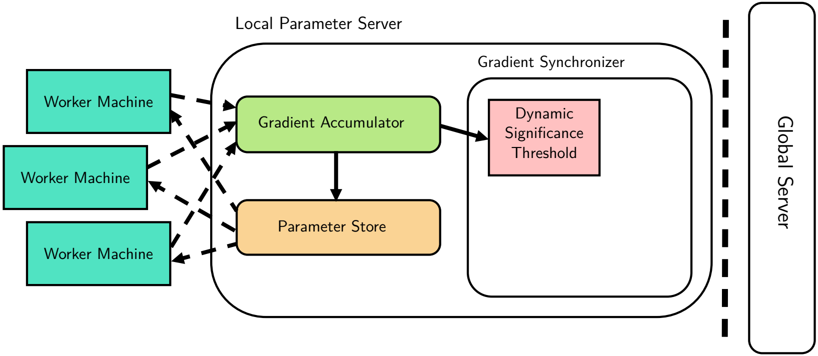

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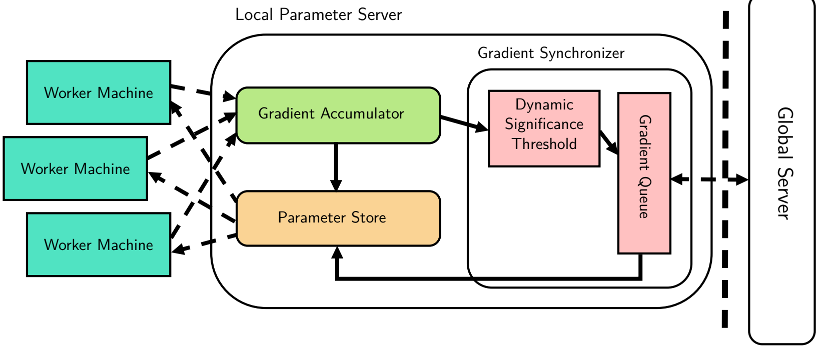

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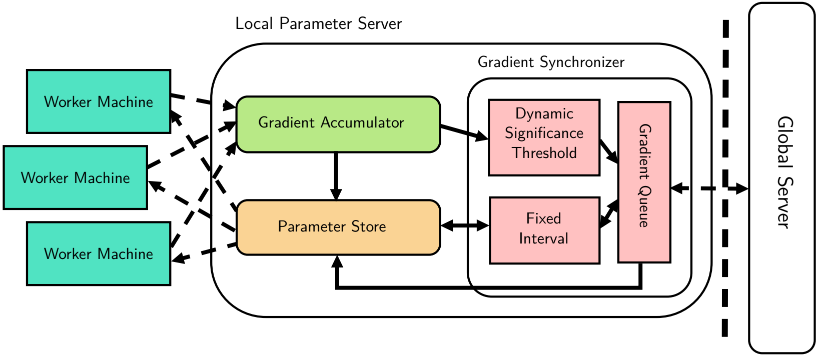

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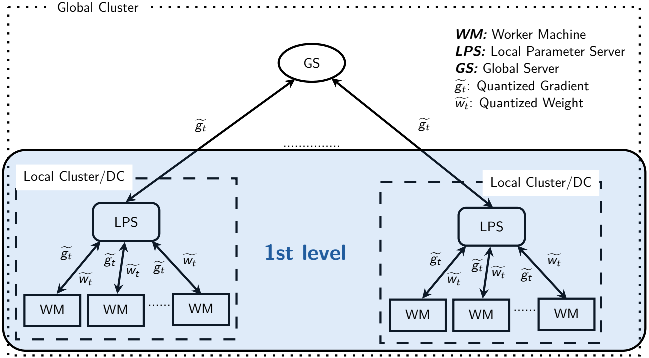
Two Level Structure



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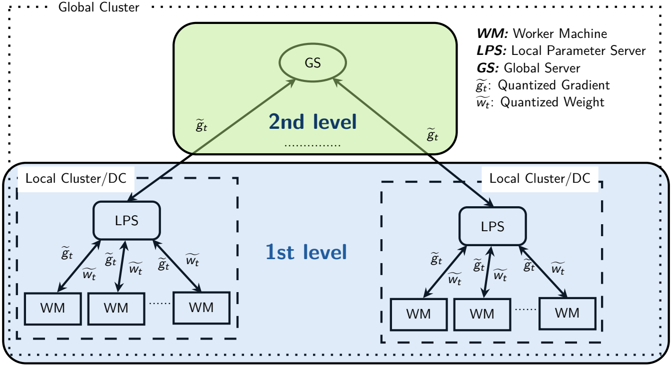

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Basic Algorithm

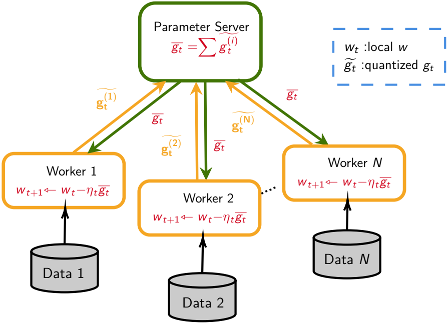

Figure: Traditional Worker-Parameter Server

- Send quantized gradients in each epoch to PS
- Workers receive average quantized gradient

WeightGrad

Worker Machine

- $\widetilde{g_s^{(i)}} = \mathit{ComputeTernarizedGradient}\left(z_s^{(i)}, W_s^{(i)}, {}_s^{(i)}\right)$
- $\mathit{SendToLPS}\left(\widetilde{g_s^{(i)}}\right)$
- $W_{s+1}^{(i)} = \mathit{ReceiveParameters}()$

Local Parameter Server

- $\overline{g_s} = \frac{1}{N}\sum_{i=1}^{N}\widetilde{g_s^{(i)}}$ N: Number of Workers
- $g_u = \mathit{AggregateGradient}\left(\overline{g_s}\right)$
- **if** $\left(\frac{g_u}{g_s} > G_{thresh}\right)$ **then** $\mathit{SendGradientToGS}(g_u)$
- $\mathit{PullGradWithinTandUpdateParameter}\left(\overline{g_u}\right)$

Global Server

- $\overline{g_u} = \frac{1}{N}\sum_{i=1}^{N} g_u^{(i)}$

  N: Number of LPS
- $\mathit{SendToAllLPS}\left(\overline{g_u}\right)$

WeightGrad Tuning

Worker Machine

- $\widetilde{g_s^{(i)}} = ComputeTernarizedGradient\left(z_s^{(i)}, W_s^{(i)}, ,_s^{(i)}\right)$
- $SendToLPS\left(\widetilde{g_s^{(i)}}\right)$
- $W_{s+1}^{(i)} = ReceiveParameters()$

Local Parameter Server

N: Number of Workers

- **for** $i \in N$
  $UpdateParameters\left(\widetilde{g_s^{(i)}}\right)$
  $g_u = AggregateGradient\,(\overline{g_s})$
- $g_{max} = MaxGradient\,(\widetilde{g_s})$
- **if** $\left(\frac{g_u}{g_{max}} > G_{thresh}\right)$ **then** $SendGradientToGS(g_u)$
- $PullGradWithinTandUpdateParameter\,(\overline{g_u})$
- **if** $(\overline{g_u} > g_{max})$ **then** $UpdateParameters\,(\overline{g_u} - g_{max})$

Global Server

- $\overline{g_u} = \frac{1}{N}\sum_{i=1}^{N} g_u^{(i)}$
  N: Number of LPS
- $SendToAllLPS\,(\overline{g_u})$

Quantized Network Accuracy

To reduce the fall of convergence rate due to gradient quantization

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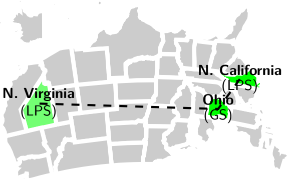
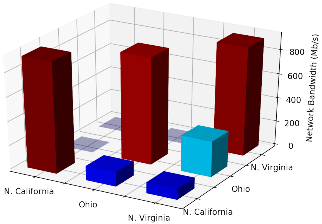
We observe that **gradient clipping with momentum correction** and **layer-wise ternarizing** gives the best convergence rate among the state-of-the-art systems.

Amazon EC-2



(a)



(b)

Figure: (a) Deployment Regions in AWS, (b) Measured network bandwidth between Amazon EC2 sites

Amazon EC-2

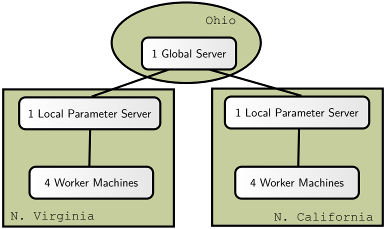
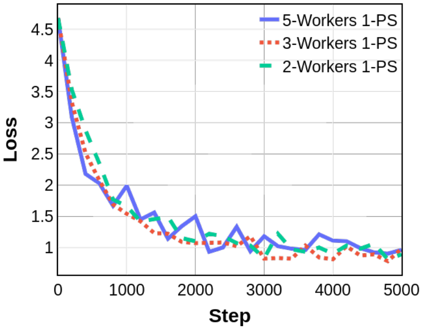


Figure: Instance Hierarchy

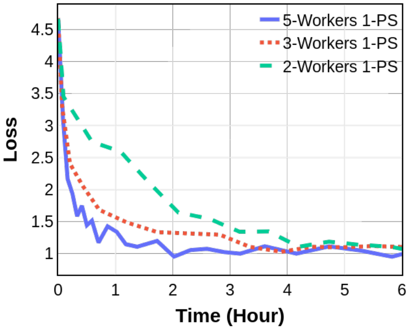
Instances	Instance Type	RAM	vCPU	GPU	B/W
11	g3s.xlarge, 64-bit Ubuntu Server 16.04 LTS	30.5 GiB	4	NVIDIA Tesla M60 GPU	10 Gbps

Table: Instance Configuration

Convergence Analysis



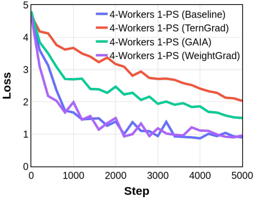
(a) Loss vs Step



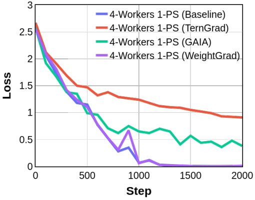
(b) Loss vs Time (hour)

Figure: Convergence of WeightGrad for CIFAR10 dataset

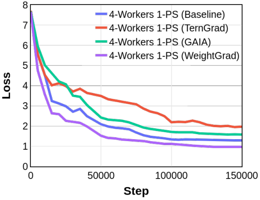
Training Loss Analysis



(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

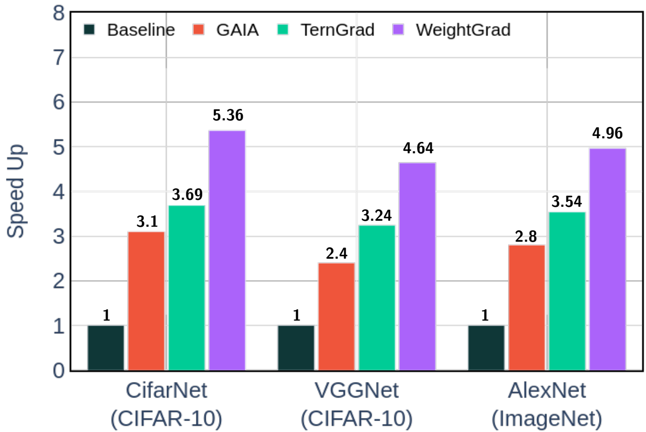


Figure: Training Speed Comparison

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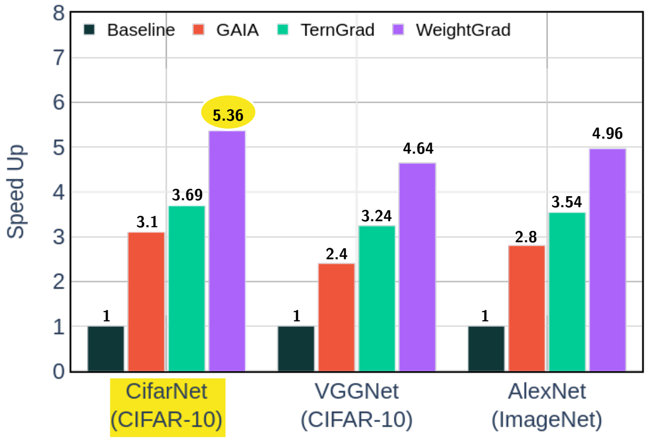

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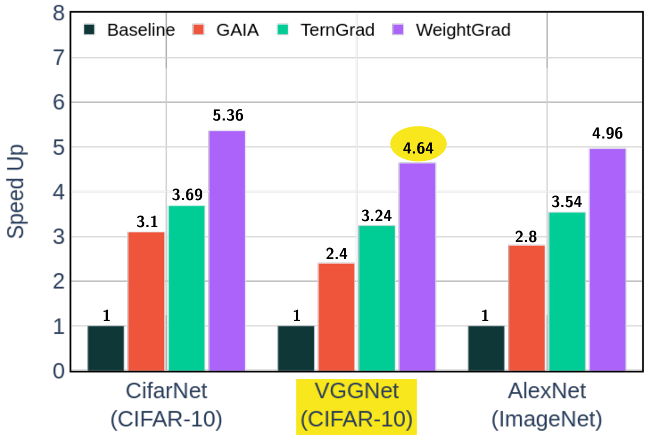

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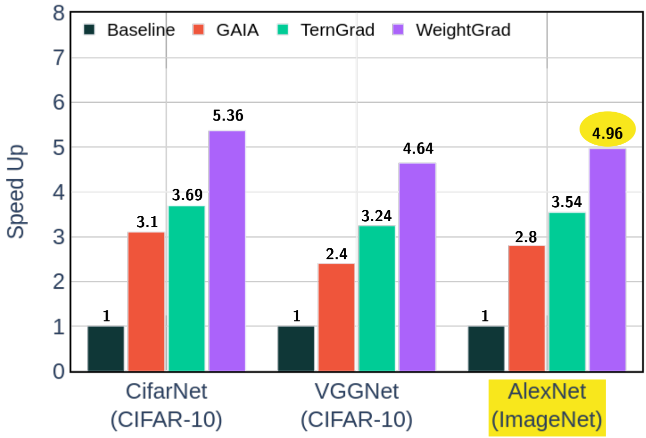

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Accuracy Comparison: CIFAR-10

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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Future Works

- Integrating XNOR-Net [Rastegari et al. (2016)] with WeightGrad back-propagation phase in parameter server.
  - XNOR-Net gives **58**$\times$ faster convolutional operations and **32**$\times$ memory savings.

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.