ElastiQuant: Elastic Quantization Strategy for Communication Efficient Distributed Machine Learning in IoT

Bharath Sudharsan

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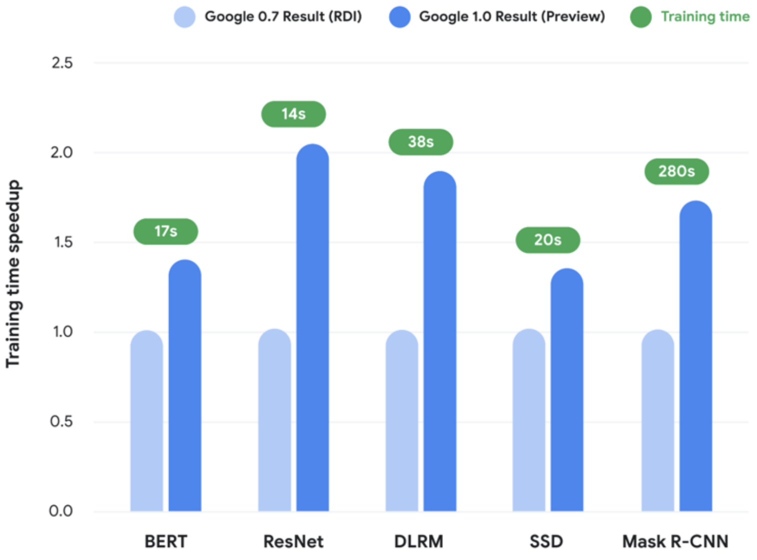
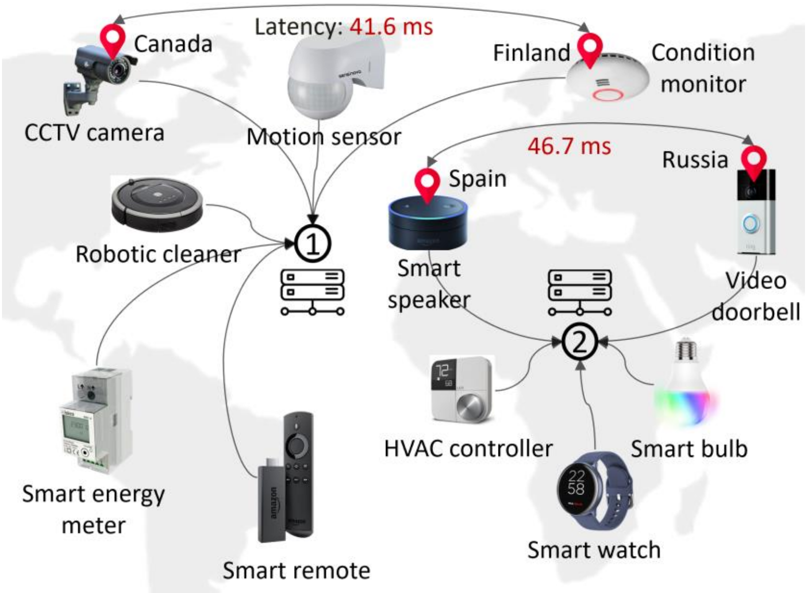
Overview



Training ML models on Google TPU Pod v4 - MLPerf



Training ML models on IoT devices - Globe2Train

- **Distributed ML in Data Centers/TPU Pods/GPU Clusters** - Train SOTA models faster, at greater scale, and at lower cost
- **Distributed ML in IoT** - On-device training with privacy preservation. Distribute neural workloads on 1000s of idle IoT devices

Related Work

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Table 1: ElastiQuant comparison with related papers. Not Applicable (NA), Not Investigated (NI), No Guarantee/assurance (NG).

Paper	Test Setup	Gradients; Momentum	Variance	Com bits	Scalability	Worst-case	Highlight
ATOMO [30]	AWS EC2 cloud	Atomic sparsification; NI	NG	Bounds	Within cluster nodes	NI	Sparsification to minimize variance
Terngrad [32]	128-node each with 4 Nvidia P100	Quantize to ternary levels; Yes	NI	NI	Within cluster nodes	NI	Need only three levels to aggressively reduce communication time
Globe2Train [20]	MCUs, CPUs	NA	NI	NI	Global IoT devices	NI	Latency, congestion tolerance
AD-PSGD [13]	32-node each with 4 Nvidia P100	NI	Bounds	NI	Within cluster nodes	NI	Robust to heterogeneity
QSGD [1]	AWS EC2 cloud	Lossy compression; NI	Bounds	Bounds	Within cluster nodes	NI	Good practical performance
NUQSGD [15]	8 NVIDIA 2080 Ti GPUs	Nonuniform quantization; Yes	Assurance, bounds	Bounds	Within cluster nodes	Yes	Stronger guarantees, higher empirical performance
D2 [27]	16 workers	NI	Assurance, bounds	NI	Within cluster nodes	NI	Much improve convergence rate, robust to data variance
EF-SignSGD [11]	Multiple workers	Error-feedback; Yes	NI	NI	Within cluster nodes	NI	Simply add EF to recover performance
DGC [14]	64-node each with 4 Nvidia Titan XP	Deep compression; Yes	NI	NI	Within cluster nodes, mobiles	NI	270 x - 600 x gradient compression ratio without losing accuracy
PowerSGD [29]	8-node each with 2 Nvidia Titan X	Low-rank compression; Yes	NI	NI	Within cluster nodes	NI	Consistent wall-clock speedups, test performance on par with SGD
ElastiQuant	18 IoT boards, edge GPUs	Elastic quantization; Yes	Assurance, bounds	Bounds	IoT boards, mobiles, edge GPUs	Yes	Higher solution quality, scalability - assurance with results

ElastiQuant Design

1. ElastiQuant Quantization Strategy
2. ElastiQuant Efficient Encoding
3. ElastiQuant Theoretical Assurance
   - Variance Bound
   - Bound on Number of Commn Bits
4. ElastiQuant with Momentum
   - For Convex Optimization
   - For Smooth Nonconvex Optimization
5. ElastiQuant for Decentralized Training
6. Worst-case Variance Analysis
   - Generally Spaced Levels
   - Exponentially Spaced Levels

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ElastiQuant Quantization Strategy

- Existing schemes that compress gradients does not take into consideration the properties of gradient vectors
  - ✓ Leads to slowing overall convergence as the gradient variance increase
  - ✓ To optimize overall performance, the communication savings should be balanced with variance
- ElastiQuant elastically distributes quantization levels in the unit interval
  - ✓ Uses a custom parameterized generalization to **control** communication cost and gradient variance
  - ✓ Reduces quantization error and variance as it can **match** the properties of gradient vectors
  - ✓ It increases the number of quantization levels near zero to obtain a **stronger** variance bound

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ElastiQuant Efficient Encoding

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ElastiQuant Theoretical Assurance

- To provide tighter bounds on the code-length:
  - ✓ ***Encode*** function encodes quantized gradients before transmission
  - ✓ Uses b bits floating point
  - ✓ b set to 4 produces 4-bit-ElastiQuant
  - ✓ In rounds, the ***Decode*** function reads b bits, uses ERC^{-1} to reconstruct gradients

- Bound on Number of Communication Bits:
  - ✓ Variance bound + code-length bound = total commn costs bound
  - ✓ Suboptimal commn **savings** as compared to other schemes
- ElastiQuant Variance Bound - models with high variance fail to generalize
  - ✓ ElastiQuant bound is **tighter** than related schemes
- Both bounds demonstrated by training ResNets on CIFAR & ImageNet

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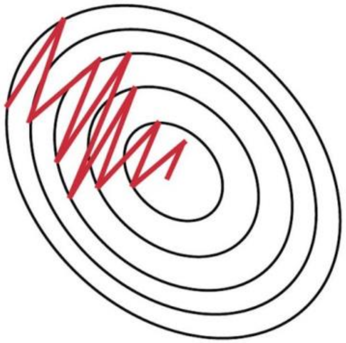
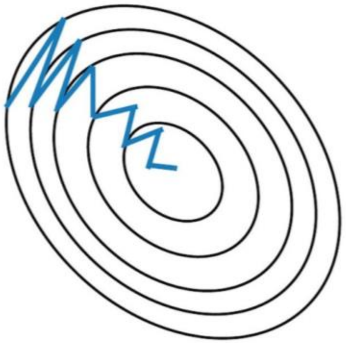


Stochastic Gradient Descent **withhout** Momentum



Stochastic Gradient Descent **with** Momentum

- Momentum helps accelerate gradients
  - ✓ Consistently in the right directions
  - ✓ Also dampens oscillations
  - ✓ Leads to faster convergence

4

ElastiQuant
with
Momentum

- Momentum is added to ElastiQuant training algorithm
- For nonconvex optimization, there can exist multiple locally optimal points - requires extra computation
- For convex optimization, there can be only one optimal solution
- We establish convergence assurance for momentum ElastiQuant for both optimizations:
  - ✓ ElastiQuant with Momentum for Convex Optimization
  - ✓ ElastiQuant with Momentum for Smooth Nonconvex Optimization

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ElastiQuant for Decentralized Training

- For gradient communication, low latency and high bandwidth cannot be guaranteed to all devices
  - ✓ ElastiQuant can **integrate** with communication-efficient variants of decentralized parallel SGD
  - ✓ Provides a solution for distributed training of deep networks in **constrained** networked systems

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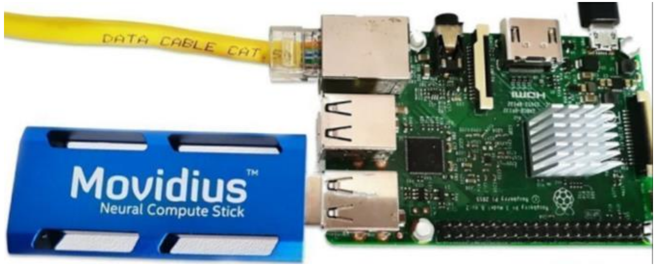
Worst-case Variance Analysis

- Incorporated into any solution selection process for a robust system design
- Performed to gain insights on the behavior of the variance upper bound
  - ✓ An upper bound for **tight worst-case** variance is established
  - ✓ Analysis shows ElastiQuant is **nearly optimal** in the worst-case
- Extend elastic quantization to arbitrary sequence of levels
  - ✓ Generally Spaced Levels
  - ✓ Exponentially Spaced Levels

Experimental Evaluation



- **Setup.** 18 development boards wirelessly set up to replicate real-world heterogeneous IoT:
  - ✓ 7 Jetson Xaviers
  - ✓ 4 Jetson Nanos inserted on a Jetson Mate carrier board
  - ✓ 3 accelerated Google Coral boards
  - ✓ 4 Intel Movidius NCS accelerated Raspberry Pi
- **Data.** Portions of ImageNet, CIFAR-10, CIFAR-100 datasets are supplied to these boards for distributed training
- **Network.** ResNet family - ResNet-18, ResNet-20, ResNet-34, ResNet-50, Resnet-110 are trained
- **Implementation.** ElastiQuant in TensorFlow

Solution Quality

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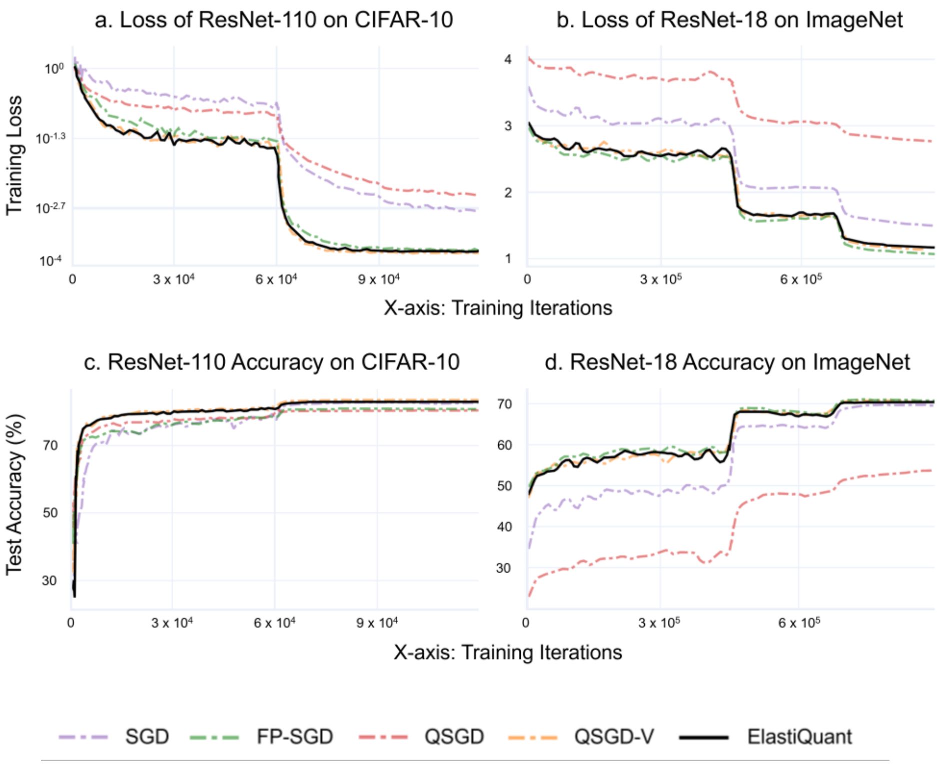

- **Training Loss -** Distributed training on 18 GPUs
  - ✓ ImageNet - ElastiQuant, QSGD-V has lower loss compared to QSGD
  - ✓ CIFAR10 - Significant gap in training loss which grows as training progresses
- **Test Accuracy**
  - ✓ Unlike ElastiQuant, QSGD does not achieve the accuracy of FP-SGD
  - ✓ For both datasets, ElastiQuant and QSGD-V outperform QSGD
  - ✓ The gap between ElastiQuant and QSGD is significant on ImageNet
  - ✓ ElastiQuant and QSGD-V show lower variance in comparison to QSGD

Scalability and Speedup Behavior

Table 3: Evaluating scalability performance of ElastiQuant by distributed training on 2 to 7 devices, and comparison with SGD: Calculating speedup (*Sp*) and total time (*T*) per epoch in minutes - sum of computation (*Cp*), encoding (*En*), transmission (*Tx*).

Network, Dataset	Scheme	2 Edge GPUs				4 Edge GPUs					7 Edge GPUs				
		Cp	*En*	*Tx*	*T*	*Cp*	*En*	*Tx*	*T*	*Sp*	*Cp*	*En*	*Tx*	*T*	*Sp*
ResNet-34, ImageNet	SGD	16.06	NA	17.93	33.99	10.47	NA	20.62	31.09	-2.9 ↑	15.34	NA	26.84	42.18	11.09 ↓
	8-bit-ElastiQuant	14.61	4.15	16.16	34.92	7.98	4.04	11.92	23.94	-10.98 ↑	10.05	4.04	10.26	25.35	1.41 ↓
	4-bit-ElastiQuant	15.75	0.93	15.55	32.23	11.19	1.25	9.32	21.76	-10.47 ↑	9.64	1.34	7.47	18.45	-3.31 ↑
	E-ElastiQuant	14.72	1.34	15.24	31.3	10.57	1.55	8.29	20.41	-10.89 ↑	8.91	1.35	6.01	16.27	-4.14 ↑
ResNet-50, ImageNet	SGD	177.23	NA	222.53	399.76	167.9	NA	265.17	433.07	33.31 ↓	85.28	NA	465.06	550.34	117.27 ↓
	8-bit-ElastiQuant	179.21	38.65	190.55	409.09	145.25	39.97	145.25	330.49	-78.62 ↑	99.94	38.64	183.89	322.47	-8.02 ↑
	4-bit-ElastiQuant	179.89	9.33	183.89	373.11	142.58	8.12	118.59	269.17	-103.94 ↑	110.6	6.66	126.59	243.85	-25.32 ↑
	E-ElastiQuant	169.23	21.32	171.9	362.45	126.59	18.66	103.93	249.18	-113.27 ↑	119.93	19.99	78.62	218.54	-30.64 ↑

- SGD **negative** scalability - *T* increases from 31.09 to 42.18 min for ResNet-34, and 433.07 to 550.34 min for ResNet-50
- 4-bit-ElastiQuant attains **positive** scalability - 1.48 times speedup for ResNet-34 when GPUs scaled from 2 to 4
- 8-bit-ElastiQuant faces a scalability **stall** when GPUs scaled from 4 to 7 - due to elevated encoding & communication costs
- E-ElastiQuant shows **top-of-the-class** scalability and communication compression

Results Comparison

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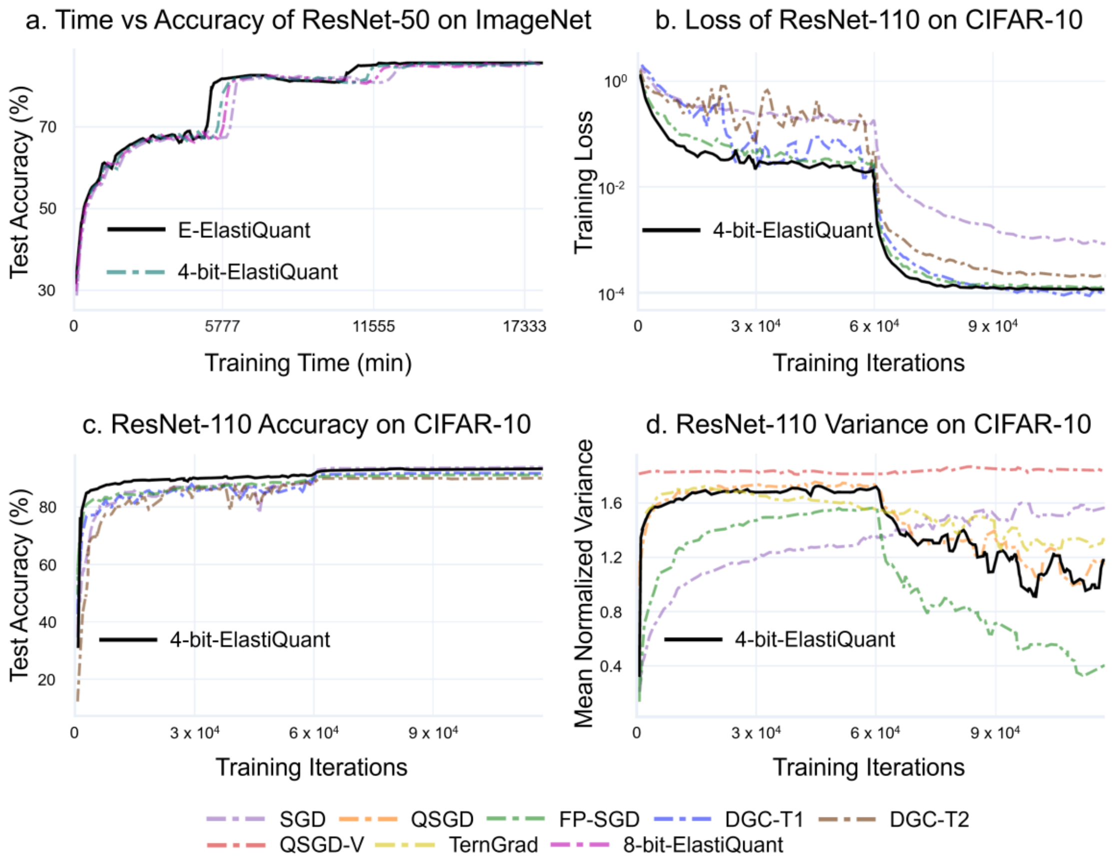

- Time vs accuracy results:
    - ✓ All ElastiQuant variants match the non-quantized ResNet-50 accuracy, with speedups over SGD (baseline)
    - ✓ QSGD-V not plotted as its performance overlaps 4-bit-ElastiQuant
- EF-SignSGD needed intensive tuning to make it converge plus to bring up its accuracy
    - ✓ Tuning makes EF-SignSGD send additional scaling data - reduced efficiency
- E-ElastiQuant offers competitive performance
    - ✓ Provides convergence assurances
    - ✓ Additional comn bandwidth savings from its gradients encoding feature

Results Comparison

Table 4: Accuracy comparison of ElastiQuant trained ResNets with models trained using DGC, compression ratio (CR) tuned DGC, Atomo, TernGrad, others. FP-SGD is baseline.

Network, Dataset	Scheme	Tune	Edge GPUs	Test Accuracy (%)
ResNet-20, CIFAR-10	Atomo	Default	2	87.6
	TernGrad			No convergence
	FP-SGD			90.5
	4-bit-ElastiQuant			86.3
ResNet-18, CIFAR-10	DGC	0.02 CR	2	91.25
			6	88.87
		0.12 CR	2	90.08
			6	87.36
	FP-SGD	Default	6	92.72
	4-bit-ElastiQuant		6	91.96
ResNet-18, CIFAR-100	DGC	0.02 CR	2	74.41
			6	72.69
	FP-SGD	Default	6	74.33
	4-bit-ElastiQuant			73.63
ResNet-110, CIFAR-10	SGD	Default	6	89.76
	QSGD			89.22
	QSGD-V			90.10
	FP-SGD			92.03
	TernGrad			91.33
	4-bit-ElastiQuant			90.80

- ElastiQuant vs Deep Gradient Compression (DGC)
  - ✓ ResNet-18 on CIFAR-10, CIFAR-100 - unlike ElastiQuant, DGC **accuracy degrades** when GPUs scaled from 2 to 4
  - ✓ So even if ElastiQuant could save lesser commn bandwidth than DGC, ElastiQuant is **practical** due to its better scalability
- ElastiQuant vs ATOMO and TernGrad
  - ✓ For ResNet-20, although ATOMO shows slightly higher accuracy than ElastiQuant, ATOMO has **high train time** plus GPU strain
  - ✓ TernGrad convergence was **under par** for standard parameters - tuning to bring performance close to ATOMO & ElastiQuant
  - ✓ For ResNet-110, TernGrad shows the closest performance to FPSGD and slightly **outperforms** 4-bit-ElastiQuant

Conclusion

- ElastiQuant improves communication efficiency during distributed learning in IoT. It consistently demonstrated:
  - ✓ Improved solution quality as the resultant ResNet models achieved **lower loss and better accuracy**
  - ✓ Higher **training scalability and speedup** due to reduced communication volume
  - ✓ Reduced quantization induced **variance** due to its elastic quantization approach
  - ✓ On-the-fly **communication efficiency** as ElastiQuant can re-use parameters of full-precision schemes with slight tuning

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Contact: Bharath Sudharsan
Email: bharath.sudharsan@insight-centre.org

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