TernGrad: Ternary Gradients to Reduce Communication in Distributed Deep Learning

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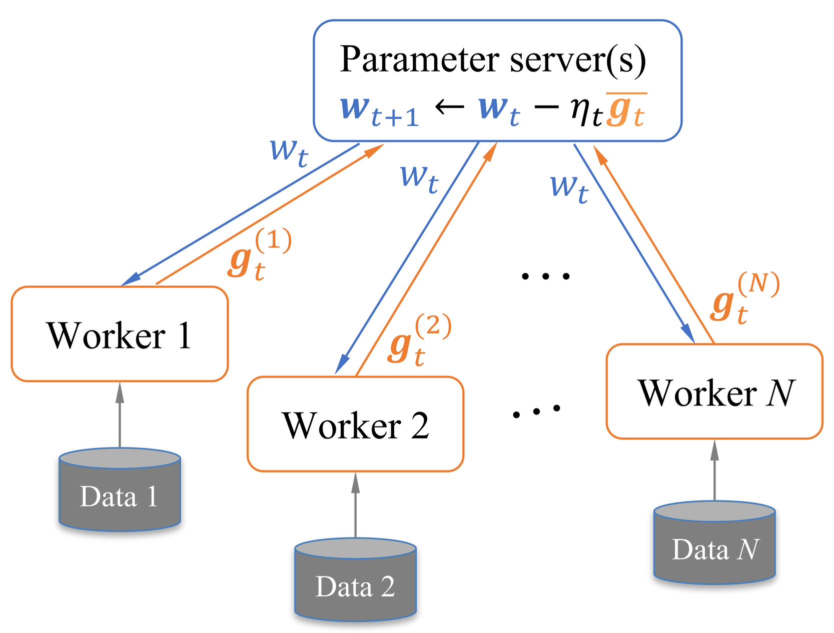
Background & Motivation

Goal

Accelerate distributed training (of deep neural networks) by overcoming communication bottleneck.

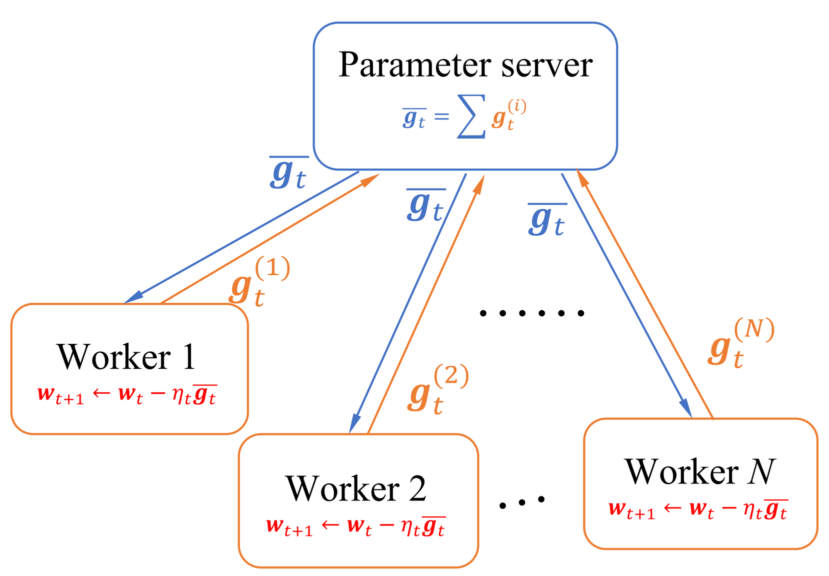


Synchronized Data Parallelism for Stochastic Gradient Descent (SGD):

1. Training data is split to N subsets
2. Each worker has a model replica (copy)
3. Each replica is trained on its subset of training data
4. Synchronization in parameter server(s)

Scalability (larger N):

1. Computing time decreases as N increases
2. Communication time becomes the bottleneck
3. This work: ternary gradients to reduce communication



An alternative setting of Synchronized Data Parallelism :

1. Only exchange gradients
2. Each worker pulls average gradients from server and update weights locally
3. Gradient quantization can reduce communication in both directions
4. An identical model across workers (ensured by using the same random seed to initialize parameters)

TernGrad and Convergence

Stochastic Gradients without Bias

Batch Gradient Descent

$$C(\boldsymbol{w}) \triangleq \frac{1}{n}\sum_{i=1}^{n} Q(\boldsymbol{z}_i, \boldsymbol{w})$$

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \frac{\eta_t}{n}\sum_{i=1}^{n} g_t^{(i)}$$

SGD

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta_t \cdot g_t^{(I)}$$

I is randomly drawn from [1,n]

$\mathrm{E}\left\{g_t^{(I)}\right\} = \nabla C(\boldsymbol{w})$ No bias

TernGrad

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta_t \cdot ternarize\left(g_t^{(I)}\right)$$

$\mathrm{E}\left\{ternarize\left(g_t^{(I)}\right)\right\} = \nabla C(\boldsymbol{w})$

No bias

$$\tilde{\boldsymbol{g}}_t = ternarize(\boldsymbol{g}_t) = s_t \cdot sign(\boldsymbol{g}_t) \circ \boldsymbol{b}_t$$

$$s_t \triangleq ||\boldsymbol{g}_t||_\infty \triangleq max(abs(\boldsymbol{g}_t))$$

$$\begin{cases} P(b_{tk} = 1 \mid \boldsymbol{g}_t) = |g_{tk}|/s_t \\ P(b_{tk} = 0 \mid \boldsymbol{g}_t) = 1 - |g_{tk}|/s_t \end{cases}$$

Example:

$g_t^{(i)}$: [0.30, -1.20, …, 0.9]

s_t: 1.20

Signs: [1, -1, …, 1]

$P(b_{tk} = 1 | g_t)$: $[\frac{0.3}{1.2}, \frac{1.2}{1.2}, …, \frac{0.9}{1.2}]$

$\widetilde{g_t^{(i)}}$: [0, -1, …, 1]*1.20

$$\mathbf{E}_{\boldsymbol{z},\boldsymbol{b}}\{\tilde{\boldsymbol{g}}_t\} = \mathbf{E}_{\boldsymbol{z},\boldsymbol{b}}\{s_t \cdot sign(\boldsymbol{g}_t) \circ \boldsymbol{b}_t\}$$

$$= \mathbf{E}_{\boldsymbol{z}}\{s_t \cdot sign(\boldsymbol{g}_t) \circ \mathbf{E}_{\boldsymbol{b}}\{\boldsymbol{b}_t | \boldsymbol{z}_t\}\} = \mathbf{E}_{\boldsymbol{z}}\{\boldsymbol{g}_t\} = \nabla_{\boldsymbol{w}} C(\boldsymbol{w}_t)$$ No bias

Convergence of standard SGD and *TernGrad* (Fisk 1965, Metivier 1981&1983, Bottou 1998)

Assumption 1: $C(\boldsymbol{w})$ has a single minimum $\boldsymbol{w}^*$ and $\forall \epsilon > 0, \inf_{||\boldsymbol{w}-\boldsymbol{w}^*||^2 > \epsilon} (\boldsymbol{w} - \boldsymbol{w}^*)^T \nabla_{\boldsymbol{w}} C(\boldsymbol{w}) > 0$

Assumption 2: Learning rate γ_t decreases neither very fast nor very slow $\begin{cases} \sum_{t=0}^{+\infty} \gamma_t^2 < +\infty \\ \sum_{t=0}^{+\infty} \gamma_t = +\infty \end{cases}$

Assumption 3: (gradient bound) $\mathbf{E}\{||\boldsymbol{g}||^2\} \le A + B\,||\boldsymbol{w} - \boldsymbol{w}^*||^2$ SGD almost truly converges | $\mathbf{E}\{||\boldsymbol{g}||_\infty \cdot ||\boldsymbol{g}||_1\} \le A + B\,||\boldsymbol{w} - \boldsymbol{w}^*||^2$ *TernGrad* almost truly converges

$\mathbf{E}\{||\boldsymbol{g}||^2\} \le \mathbf{E}\{||\boldsymbol{g}||_\infty \cdot ||\boldsymbol{g}||_1\} \le A + B\,||\boldsymbol{w} - \boldsymbol{w}^*||^2$ Stronger gradient bound in *TernGrad*

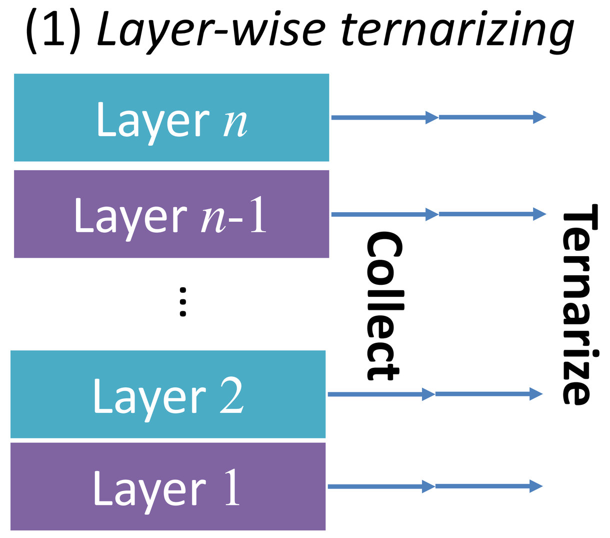
Gradient Bound and Variance

Two views to improve the convergence of *TernGrad*:

1. Variance
   - ✓ Relatively smaller $||g_t||_\infty$ can achieve smaller gradient variance
2. Gradient Bound
   - ✓ Relatively smaller $||g_t||_\infty$ pushs gradient bound (**Assumption 3**) of *TernGrad* closer to the one of standard SGD

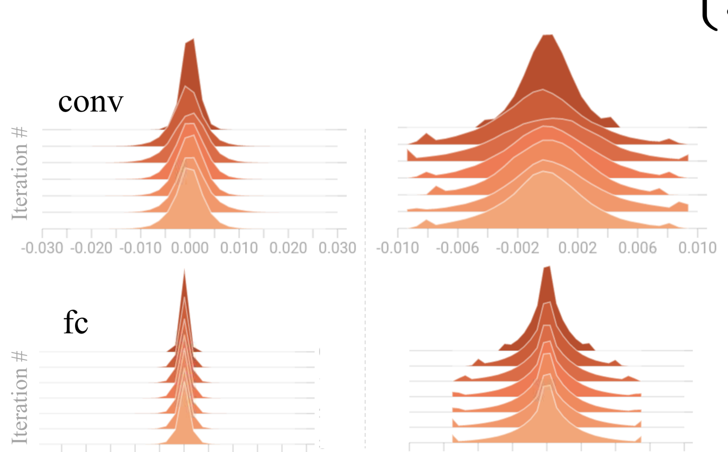
Two methods to push gradient bound closer:

(1) *Layer-wise ternarizing*



Extreme case: ternarizing gradient one by one is just the floating SGD

(2) *Gradient clipping* $f(g_i) = \begin{cases} g_i & |g_i| \le c\sigma \\ sign(g_i) \cdot c\sigma & |g_i| > c\sigma \end{cases}$



(a) original (b) clipped

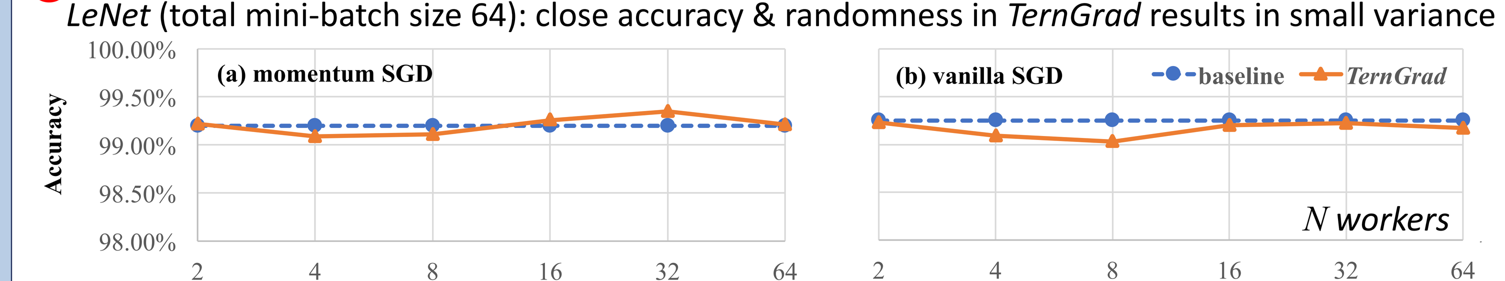
Suppose Gaussian distribution with standard deviation σ

c=2.5 works well for all tested datasets, DNNs and optimizers. Why? It

1. changes length 1%-1.5%
2. changes direction 2° -3°
3. is variance reduction method with very small bias

Experiments

① *LeNet* (total mini-batch size 64): close accuracy & randomness in *TernGrad* results in small variance



CIFAR-10, mini-batch size 64 per worker (all hyper-parameters are the same)

SGD	base LR	total mini-batch size	iterations	gradients	workers	accuracy
Adam	0.0002	128	300K	floating *TernGrad*	2 2	86.56% 85.64% (-0.92%)
Adam	0.0002	2048	18.75K	floating *TernGrad*	16 16	83.19% 82.80% (-0.39%)

D. P. Kingma, 2014

② *TernGrad*: Randomness & regularization (in large-scale dataset like ImageNet) → (1) decrease randomness in dropout or (2) use smaller weight decay

No new hyper-parameters added

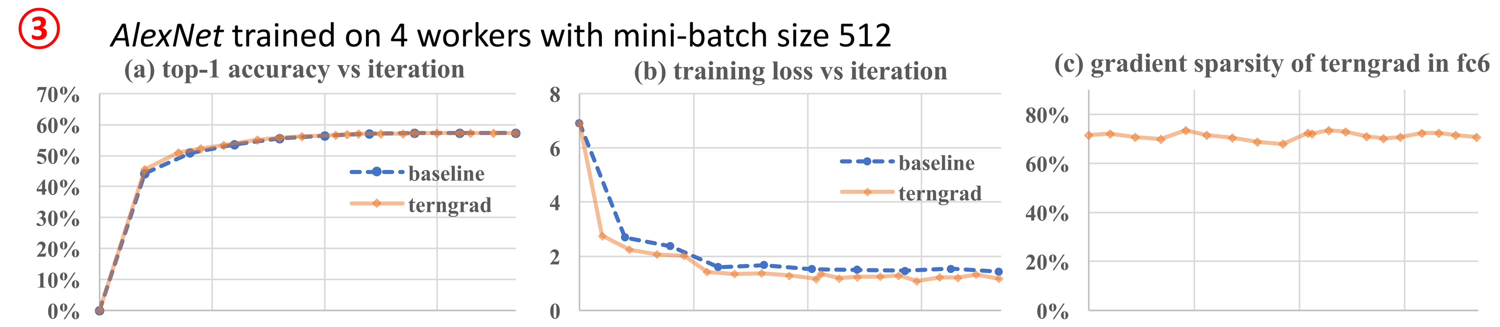
AlexNet

base LR	mini-batch size	workers	iterations	gradients	weight decay	DR†	top-1	top-5
0.01	256	2	370K	floating *TernGrad* *TernGrad*-noclip ‡	0.0005 0.0005 0.0005	0.5 0.2 0.2	57.33% 57.61% 54.63%	80.56% 80.47% 78.16%
0.02	512	4	185K	floating *TernGrad*	0.0005 0.0005	0.5 0.2	57.32% 57.28%	80.73% 80.23%
0.04	1024	8	92.5K	floating *TernGrad*	0.0005 0.0005	0.5 0.2	**56.62%** **57.54%**	80.28% 80.25%

† DR: dropout ratio, the ratio of dropped neurons. ‡ *TernGrad* without gradient clipping.

Noise in TernGrad helps SGD escaping from sharp minima when batch size is large (N. S. Keskar, ICLR 2017)

③ *AlexNet* trained on 4 workers with mini-batch size 512



GoogLeNet (<2% accuracy loss on average)

base LR	mini-batch size	workers	iterations	gradients	weight decay	DR	top-5
0.04	128	2	600K	floating *TernGrad*	4e-5 1e-5	0.2 0.08	88.30% 86.77%
0.08	256	4	300K	floating *TernGrad*	4e-5 1e-5	0.2 0.08	87.82% 85.96%
0.10	512	8	300K	floating *TernGrad*	4e-5 2e-5	0.2 0.08	89.00% 86.47%

All other hyper-parameters are tuned for standard SGD and fixed in TernGrad

Tune hyper-parameters specifically for *TernGrad* may reduce accuracy loss

④ A performance model to evaluate the speedup