Practical Low-Rank Communication Compression in Decentralized Deep Learning

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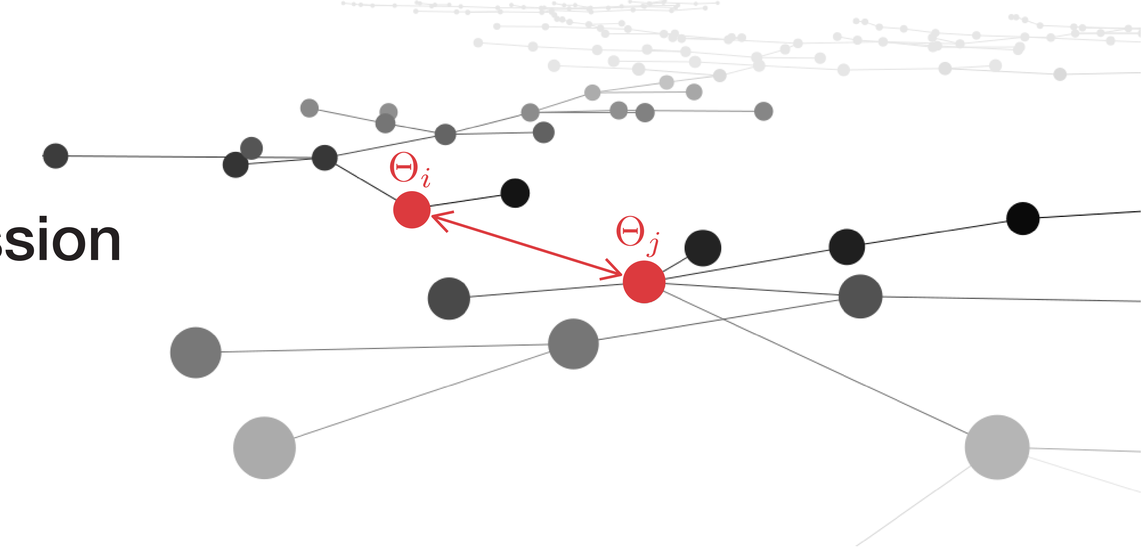

PowerGossip reduces communication between workers in decentralized learning. It converges faster than related approaches and is easier to use. It matches the quality of state-of-the-art methods with less hyper-parameter tuning.

Decentralized training

- Sparsely connected **network of workers** with their own data. They communicate only with **few 'neighbors'**. Updates diffuse slowly through the network.
- The worker's parameters are **not synchronized**: everyone computes gradients using **different models**.
- A worker i does **updates** $\Theta_i \leftarrow \Theta_i - \eta \nabla f_i^{\xi}(\Theta_i)$
  and **averages** with others $\Theta_i \leftarrow \Theta_i + \sum_{j \in \mathcal{N}_i} w_{ij}(\Theta_j - \Theta_i)$ (weights based on the network)

Lossy gradient compression

- Because neural networks and their **gradients** can be gigabytes **large**, **communication** between workers can be a **performance bottleneck** in multi-worker training.
- **Lossy compression** is an attractive solution for this.
  - In the **centralized setting**, with fully-connected workers that always agree on the model parameters, this is a **practical** and **established** approach.
  - In the **decentralized setting**, methods require an additional **consensus step size** for convergence.

No additional hyper-parameters

- Contrary to related work, **PowerGossip** has **no consensus step size hyper-parameter** and works with the same learning rate as in the centralized setting.

PowerGossip

Approximating edge-wise differences

- PowerGossip **compresses parameter differences** between neighboring workers:

$$\Theta_i \leftarrow \Theta_i + \sum_{j \in \mathcal{N}_i} w_{ij} \mathcal{C}(\Theta_j - \Theta_i)$$

- Because Θ_i and Θ_j are on **different machines**, directly compressing the difference is only **possible** because PowerGossip uses a **linear** low-rank **compressor**.

Linear low-rank compression

- Based on **PowerSGD** (Vogels et al. 2019).
- The **weights** Θ of any neural network layer can be considered **matrix-shaped**. Its rows and columns correspond to the layer's inputs and outputs.
- For a normalized **vector** v, $vv^\top M$ **approximates** M.
- Workers can exchange **small vectors** instead of **matrices**:

$$vv^\top(\Theta_2 - \Theta_1) = v(v^\top\Theta_2 - v^\top\Theta_1)$$

(Just a vector; Just a vector)

Power iteration

- The **quality** of approximation depends on the vector v. The approximation is **optimal** if v is the top eigenvector.
- The output of $v^\top(\Theta_2 - \Theta_1)$ can be used as a **better-than-random** vector for the next iteration, **improving our results empirically**. These are like steps of power iteration.
- The **strength of the compression** can be controlled through the **number** of power iteration **steps** per round.

Theoretical results

- PowerGossip **consensus** has a **Q-linear rate.** The rate depends linearly on both the compression quality and on the spectral gap of the network. Related work has a **slower rate** with quadratic dependence on the **network.**
- Our convergence rate in **decentralized SGD** is asymptotically **independent** of the **compression rate** (number of averaging steps) and **network properties**.

Experimental results

- Experiments on **image classification** with a ResNet-18 and **language modeling** with an LSTM.
  - PowerGossip achieves a **similar accuracy** as alternative methods but with **no new hyper-parameters to tune**.
  - We can use the **same learning rate** as uncompressed, centralized SGD. This is possible in the same number of iterations as long as the compression is not too strong.

CIFAR-10 in a 16-worker ring topology (300 epochs):

Algorithm	η (l.r.)	γ	θ	Test accuracy	Sent/epoch
Uncompressed (DP-SGD)	tuned			92.1%	102 MB
Choco (Sign+Norm)	tuned	tuned		92.0%	3.2 MB (32×)
Moniqua (2-bit)	tuned	tuned	tuned	90.7%	6.4 MB (16×)
DeepSqueeze (Sign+Norm)	tuned	tuned		91.2%	3.2 MB (32×)
PowerGossip (1 iteration)	default			91.7%	1.8 MB (57×)
PowerGossip (2 iterations)	default			91.9%	3.0 MB (34×)

learning rate η, averaging stepsize γ

Code

Download the code at github.com/epfml/powergossip.