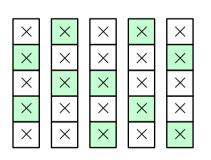


TAMUNA: Doubly Accelerated Federated Learning with Local Training, Compression, and Partial Participation

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TAMUNA

input: stepsizes $\gamma > 0$, $\eta > 0$; number of participating clients $c \in \{2, ..., n\}$ sparsity index $s \in \{2, ..., n\}$ for compression initial model estimate $\bar{x}^0 \in \mathbb{R}^d$ initial control variates $h_i^0 \in \mathbb{R}^d$ s.t. $\sum_{i=1}^n h_i^0 = 0$ **for** r = 0, 1, ... (rounds) **do** choose a subset $\Omega^r \in [n]$ of size cchoose the number of local steps L^r **for** clients $i \in \Omega^r$, in parallel, **do** $x^{r,0} := \bar{x}^r$ for $l = 0, ..., L^r$ do $x_i^{r,l} := x_i - \gamma g_i^{r,l} + \gamma h_i^r \text{ with } g_i^{r,l} \approx \nabla f_i^t(x_i^{r,l})$ send $v_i^r := C_i^r(x_i^{r,L^r})$ to server // uplink comm. end for at server: $\bar{x}^{r+1} := \frac{1}{s} \sum_{i \in \Omega^r} v_i^r$ // model update \bar{x}^{r+1} is sent to clients $i \in \Omega^r \cup \Omega^{r+1}$ // downlink comm. **for** clients $i \in \Omega^r$, in parallel, **do** // update of $h_i^{r+1} := h_i^r + \frac{\eta}{\gamma} \left(C_i^r (\bar{X}^{r+1}) - V_i^r \right)$ control variates **for** clients $i \notin \Omega^r$, in parallel, **do** $h_{i}^{r+1} := h_{i}^{r}$ // idle clients end for end for



 C_i^r : random selectors with

- *s* (=2) comm. values per coordinate
- $\leq \lceil \frac{sd}{c} \rceil$ (=2) comm. values per active client

With $\gamma \approx \frac{1}{L}$, $s \approx \max\left(2, \frac{c}{d}, \alpha c\right)$, $L^r \approx \max\left(\sqrt{\frac{s\kappa}{n}}, 1\right)$, $\eta \approx \frac{1}{2L^r}$, $g_i = \nabla f_i$, TotalCom (= UpCom + α .DownCom) complexity of TAMUNA in #floats:

$$\mathcal{O}\left(\left(\sqrt{d\sqrt{\kappa}}\sqrt{\frac{n}{c}} + d\sqrt{\kappa}\frac{\sqrt{n}}{c} + d\frac{n}{c} + \sqrt{\alpha}\,d\sqrt{\kappa}\sqrt{\frac{n}{c}}\right)\log\epsilon^{-1}\right)$$

→ New SOTA with double acceleration

Distributed optimization with *n* clients + server:

$$\underset{x \in \mathbb{R}^d}{\text{minimize}} \ f(x) := \frac{1}{n} \sum_{i=1}^n f_i(x)$$

Every f_i is \mathcal{L} -smooth and μ -strongly convex. $\kappa := \frac{\mathcal{L}}{\mu}$

Algorithms with Local Training (LT) or Compressed Communication (CC), in case of full participation:

Algorithm	LT	CC	uplink comm.
DIANA	X	✓	$\widetilde{\mathcal{O}}((1+\frac{d}{n})\kappa+d)$
EF21	X	✓	$\widetilde{\mathcal{O}}(d\kappa)$
Scaffold	1	X	$\widetilde{\mathcal{O}}(oldsymbol{d}\kappa)$
FedLin	1	X	$\widetilde{\mathcal{O}}(oldsymbol{d}\kappa)$
S-Local-GD	✓	X	$\widetilde{\mathcal{O}}(oldsymbol{d}\kappa)$
Scaffnew	1	X	$\widetilde{\mathcal{O}}(extsf{d}\sqrt{\kappa})$
5GCS	✓	X	$\widetilde{\mathcal{O}}(extsf{d}\sqrt{\kappa})$
FedCOMGATE	/	1	$\widetilde{\mathcal{O}}(oldsymbol{d}\kappa)$
TAMUNA	✓	✓	$\widetilde{\mathcal{O}}\left(\sqrt{d}\sqrt{\kappa}+d\frac{\sqrt{\kappa}}{\sqrt{n}}+d\right)$

(full participation: TAMUNA reverts to CompressedScaffnew [Condat et al. 2022])

Algorithms with LT or CC, and allowing for Partial Participation:

Algorithm	LT	CC	uplink communication
DIANA-PP	X	✓	$\widetilde{\mathcal{O}}\left((1+\frac{d}{c})\kappa+d\frac{n}{c}\right)$
Scaffold	✓	X	$\widetilde{\mathcal{O}}(d\kappa + d\frac{n}{c})$
5GCS	✓	X	$\widetilde{\mathcal{O}}\left(d\sqrt{\kappa}\sqrt{\frac{n}{c}}+d\frac{n}{c}\right)$
TAMUNA	✓	✓	$\widetilde{\mathcal{O}}\left(\sqrt{d}\sqrt{\kappa}\sqrt{\frac{n}{c}}+d\sqrt{\kappa}\frac{\sqrt{n}}{c}+d\frac{n}{c}\right)$

