Secure Aggregation Meets Sparsification in Decentralized Learning

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Motivation

Secure aggregation [1]:

- Adds communication overhead
- Makes compression hard
- Is not compatible with sparsification out of box

Privacy at the cost of communication overhead

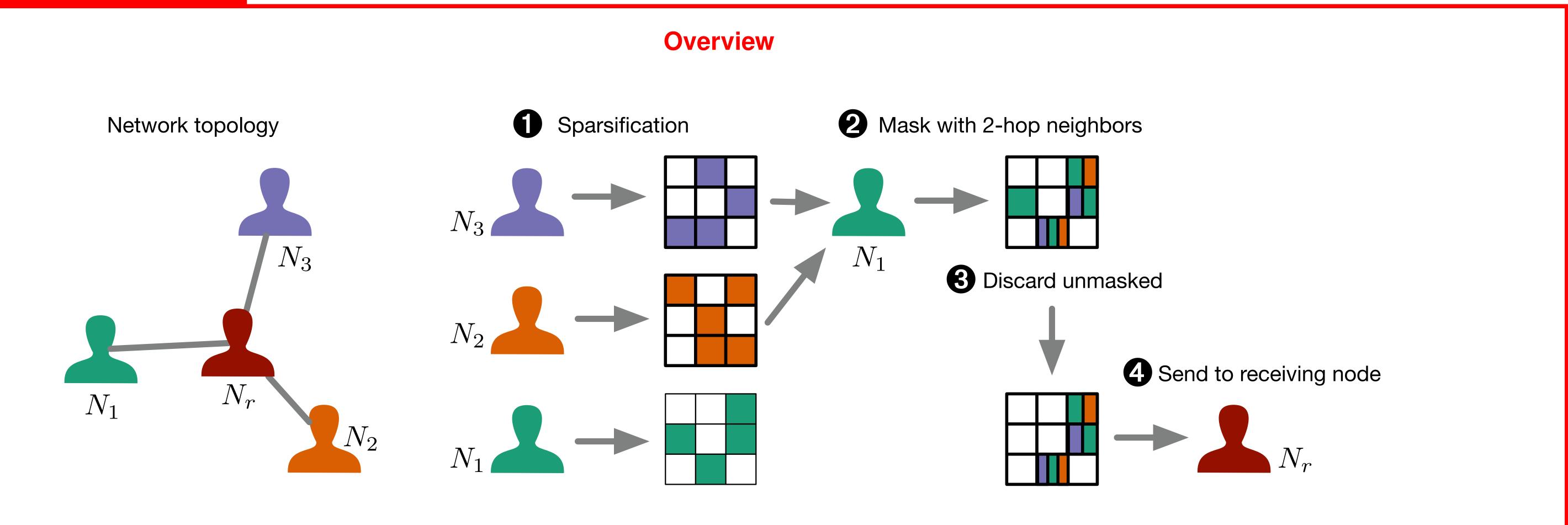
Pairwise additive masking

For $\forall a, b \in \mathbb{R}$ and $\forall c \in \mathbb{R}$:

$$a + b = (a + c) + (b - c)$$

Adding and subtracting a randomly selected number from a sum does not change its value

CESAR



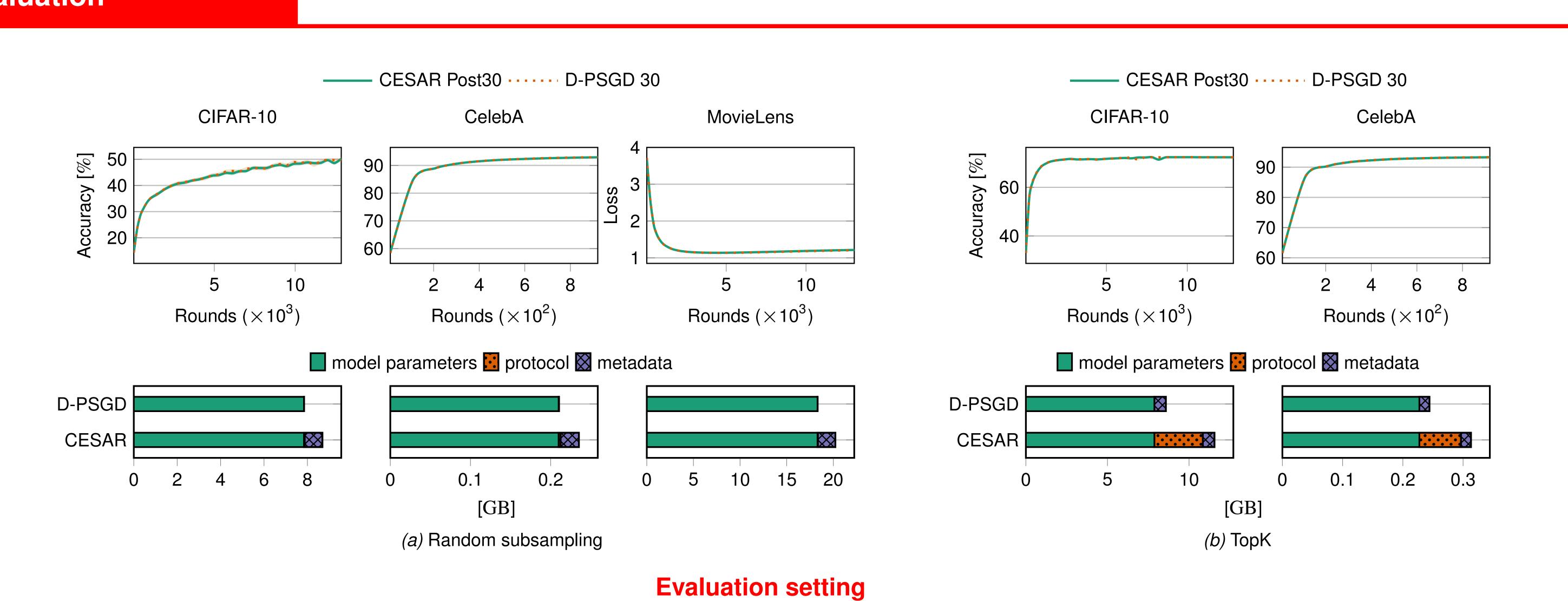
Algorithm

- Performed after sparsification
- Performed in two stages:
- Prestep: Second degree neighbours coordinate to mask mutually selected indices before sending them to the common neighbor
- Model exchange and aggregation: Indices with less than s masks applied are discarded before transmitting the model (s called masking requirement)
- Masks cancel out upon plain averaging

Properties

- 1. Privacy guarantees:
 - CESAR is resilient against honest-but-curious adversaries
 - CESAR is resilient against collusion
- 2. Communication overhead:
 - Prestep (protocol overhead): $O(\alpha d\delta_{\max}^2)$ (α percentage of selected parameters; d total number of parameters; δ_{\max} maximum degree in the network)

Evaluation



• Datasets: CIFAR, CelebA, MovieLens

Baseline: D-PSGD [2]Masking requirement (s): 1

- Data distribution: IID with TopK, NIID with random subsampling
- Network size: 96 nodesTopology: 6-regular
- [1] Keith Bonawitz et al. "Practical secure aggregation for privacy-preserving machine learning". In: proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security. 2017, pp. 1175–1191.
- [2] Lin Xiao and Stephen Boyd. "Fast linear iterations for distributed averaging". In: Systems & Control Letters 53.1 (2004), pp. 65–78. ISSN: 0167-6911. DOI: 10.1016/j.sysconle.2004.02.022.