

Extra Experiments

In this experiments, we compare our new algorithm **DASHA-PP** with previous baselines **MARINA** and **FRECON** in the partial participation setting (the comparisons of **DASHA-PP** with **DASHA** we present in Section A of the paper). We consider **MARINA** and **FRECON** because they are the previous SOTA methods in the *partial participation setting with compression*. We investigate the same optimization problem and setup as in Section A of the paper. One can find the details (loss functions, exact parameters) in Section A. All methods use the RandK compressor in these experiments.

1. Finite-Sum Setting. In Figures 1 and 2, we compare all three methods in the finite-sum setting (we use the function from Lines 408-409 of the paper) on two different datasets: *real-sim* and *MNIST*. The parameter s is the number of clients participating in each round that are selected randomly using the s -nice sampling (server chooses uniformly s nodes without replacement). We can see that **DASHA-PP** converges faster than **MARINA**. Since **FRECON** does not support variance reduction of stochastic gradients, it converges to less accurate solutions.

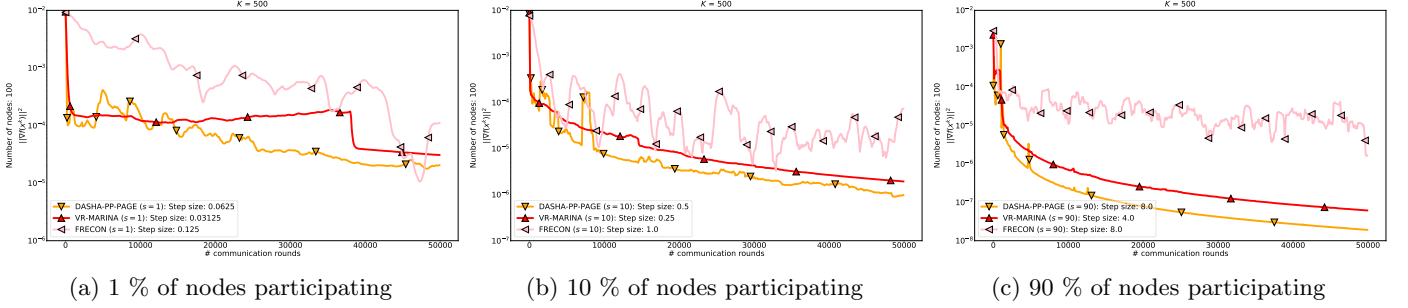


Figure 1: Classification task on *real-sim*

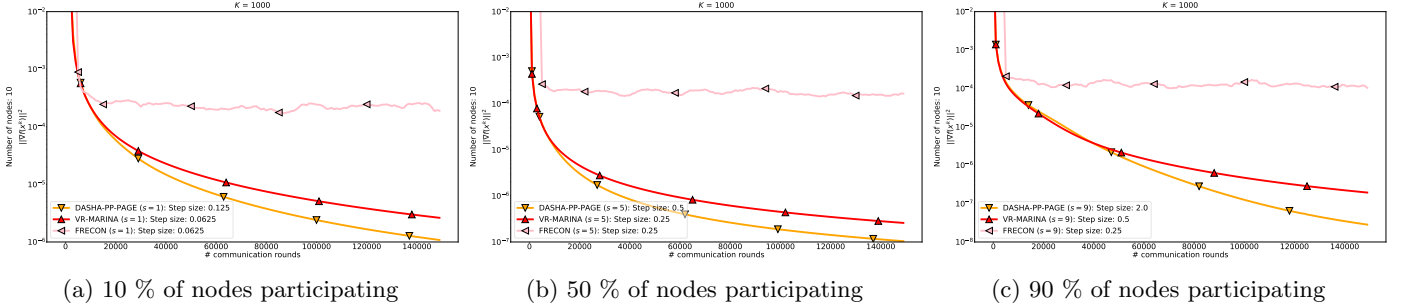


Figure 2: Classification task on *MNIST*

2. Stochastic Setting. In Figures 3 and 4, we consider the stochastic setting (we use the function from Lines 411-412 of the paper). We can see that **DASHA-PP** converges to high accuracy solutions, unlike **FRECON**. Moreover, **DASHA-PP** improves the convergence rates of **MARINA**.

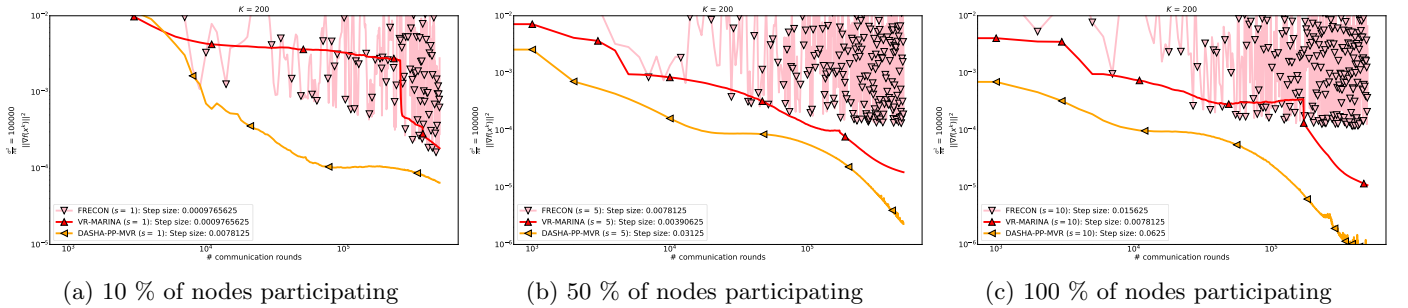


Figure 3: Classification task on *real-sim*

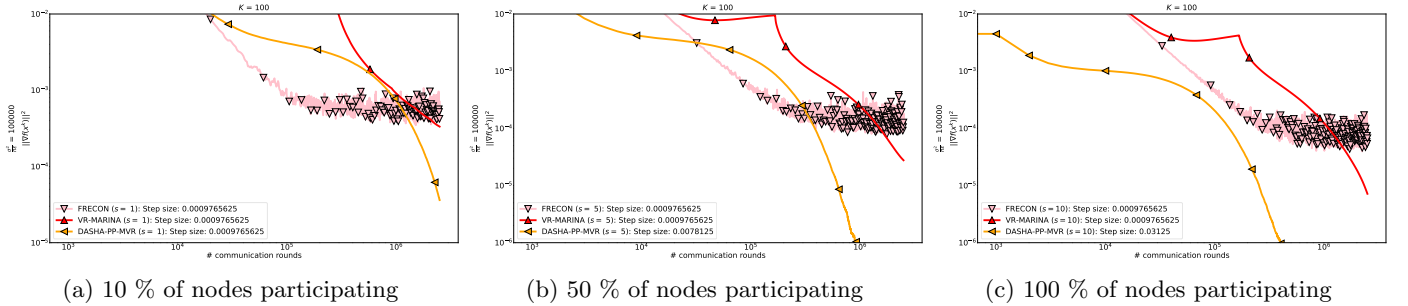


Figure 4: Classification task on *MNIST*