# Randomized Block Proximal Methods for Distributed Stochastic Big-Data Optimization

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Considering the increasing dimension of data and the limited bandwidth of communication links, classical distributed algorithms may no longer be practical. Inspired by this, the authors propose a class of distributed proximal algorithms with block-wise communication, for solving stochastic convex optimization problems with nonsmooth objective functions over a directed strongly connected communication graph. At each iteration, each node may be idle with a certain probability and only awake nodes have to exchange with their out-neighbors only a random block of its decision variable. Therefore, the proposed algorithm solves the problem caused by synchronization delay and alleviates the communication payload at each iteration. However, each node has to maintain a local solution estimate and a local copy of the solution estimates of its in-neighbors and utilizes them and updated information transmitted by in-neighbors to perform the consensus step. Due to the additional local copy, the proposed algorithm may incur more storage and memory costs. The analysis for the proposed algorithm involves two parts: When constant step-sizes are used, the generated sequence of decision variables will converge to a neighborhood of optimal solution at a sublinear rate of convergence, while asymptotic exact convergence is reached for diminishing step-sizes. Moreover, the authors illustrate the effectiveness of the proposed algorithm via a synthetic dataset and a real, high-dimensional, text document dataset.