Paper Review: A Randomized Block Subgradient Approach to Distributed Big Data Optimization

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In recent years, the growing size of networks motivates the development of distributed optimization, where data processing and computing are to be performed in a cooperative way. However, most of the existing works may not be applicable since the dimension of the decision variable is significantly increasing in the era of big data. Motivated by this, the authors develop a distributed algorithm for big data convex optimization problems with nonsmooth objective functions, in which, at each iteration, only a few blocks of the entire (local) solution estimates are exchanged among the agents over static directed networks. In this algorithm, each agent first performs a consensus step with a doubly stochastic matrix, computes a subgradient update on a randomly chosen block and then broadcasts to its neighbors only the updated block, at each iteration. It is worth noting that, despite the double stochasticity of the weight matrix, the consensus step on each block turns out to be performed with a sequence of random row-stochastic matrices. Furthermore, to derive the convergence, the authors assume that the block choices among agents are independent and identically distributed and the subgradient of each local objective function is bounded. With such assumptions, the authors first show that agents in the network asymptotically reach consensus in expected value, and then show that the minimum of the expected value of the function value converges to the optimal value asymptotically. Finally, they illustrate the convergence performance via an example of a regularized logistic regression problem.