The Regularized Stochastic Nesterov's Accelerated Quasi-Newton Method with Applications

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Abstract

The stochastic Broyden–Fletcher–Goldfarb–Shanno (BFGS) method has effectively solved strongly convex optimization problems. However, this method frequently encounters the near-singularity problem of the Hessian. Additionally, obtaining the optimal solution necessitates a long convergence time. In this talk, we present a regularized stochastic Nesterov's accelerated quasi-Newton method that combines Nesterov acceleration with a novel momentum coefficient to effectively accelerate convergence speed and avoid the near-singularity problem of the Hessian update in the stochastic BFGS method. Moreover, we show the almost sure convergence of the generated subsequence of iterates to an optimal solution of the strongly convex optimization problems. We examined our approach to real-world datasets. The experiment results confirmed the effectiveness and superiority of the proposed method compared with other methods in solving classification problems.

Keywords

Strongly convex optimization, Nesterov's accelerated gradient, Quasi-Newton method, Momentum coefficient, Support vector machine