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Beating the Saturation of The Stochastic Gradient Descent for Linear Inverse Problems

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Stochastic gradient descent (SGD) is a promising method for solving large-scale inverse problems, due to its excellent scalability with respect to data size. The current mathematical theory in the lens of regularization theory predicts that SGD with a polynomially decaying stepsize schedule may suffer from an undesirable saturation phenomenon, i.e., the convergence rate does not further improve with the solution regularity index when it is beyond a certain range. In this talk, I will present our recent results on beating this saturation phenomenon [1,2]:
(i) By using a small initial step size. We derive a refined convergence rate analysis of SGD, which shows that saturation does not occur if the initial stepsize of the schedule is sufficiently small.
(ii) By using Stochastic variance reduced gradient (SVRG), a popular variance reduction technique for SGD. We prove that, with a suitable constant step size schedule, SVRG can achieve an optimal convergence rate in terms of the noise level (under suitable regularity conditions), which means the saturation does not occur.

References:

[1] B. Jin, Z. Zhou and J. Zou, SIAM/ASA J. Uncertain. Quant., 9(4), 1553-1588 (2021).
[2] B. Jin, Z. Zhou and J. Zou, Inverse Problems, 38(2):025009, 34 (2022).