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NEW TIGHT BOUNDS FOR SGD WITHOUT VARIANCE ASSUMPTION: A COMPUTER-AIDED LYAPUNOV ANALYSIS

DANIEL CORTILD, **LUCAS KETELS**, JUAN PEYPOUQUET, AND GUILLAUME GARRIGOS

The analysis of Stochastic Gradient Descent (SGD) often relies on making some assumption on the variance of the stochastic gradients, which is usually not satisfied or difficult to verify in practice. This work [1] contributes to a recent line of works which attempt to provide guarantees without making any variance assumption, leveraging only the (strong) convexity and smoothness of the loss functions. In this context, we prove new theoretical bounds derived from the monotonicity of a simple Lyapunov energy, improving the current state-of-the-art and extending their validity to larger step-sizes. Our theoretical analysis is backed by a Performance Estimation Problem analysis [2], which allows us to claim that, empirically, the bias term in our bounds is tight within our framework.

References

[1] Cortild, D., Ketels, L., Peypouquet, J., & Garrigos, G. (2025). New Tight Bounds for SGD without Variance Assumption: A Computer-Aided Lyapunov Analysis. arXiv preprint arXiv:2505.17965.

[2] Taylor, A., & Bach, F. (2019). Stochastic first-order methods: Non-asymptotic and computer-aided analyses via potential functions. Proceedings of the 32nd Conference on Learning Theory, 2934–2992.

University of Groningen, Netherlands., email: d.cortild@rug.nl

University of Groningen, Netherlands. and Université Paris Cité and Sorbonne Université, CNRS, Laboratoire de Probabilités, Statistique et Modélisation, Paris, France., email: l.ketels@rug.nl.

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