Sign SGD with Heavy-Tailed Noise and Differential Privacy

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Abstract

For now, see a separate file for it.

1 Introduction

In the recent work [2], the authors have shown that Sign-SGD with heavy-tailed noise achieves optimal convergence rates under certain assumptions. Additionally, [1] demonstrated that Sign-SGD can be made differentially private while maintaining good convergence properties.

2 Theory

Present your theoretical framework, definitions, lemmas, and proofs.

3 Experiments

Describe your experimental setup, methodology, and results.

4 Conclusion

Summarize your findings and discuss future work.

Acknowledgments

Optional acknowledgments section.

A Additional Proofs and Results

Include detailed proofs and supplementary materials here.

References

[1] Richeng Jin et al. “Stochastic-Sign SGD for Federated Learning with Theoretical Guarantees”. In: *Part of this work is published in IEEE Transactions on Neural Networks and Learning Systems, 2024* 36.2 (Feb. 25, 2020), pp. 3834–3846. ISSN: 2162-2388. DOI: `10.1109/tnnls.2023.3345367`. arXiv: `2002.10940 [cs.LG]`.

[2] Nikita Kornilov et al. *Sign Operator for Coping with Heavy-Tailed Noise: High Probability Convergence Bounds with Extensions to Distributed Optimization and Comparison Oracle*. 2025. DOI: `10.48550/ARXIV.2502.07923`.