Generalized Linear Bandits with Local Differential Privacy

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Contextual bandit algorithms are useful in personalized online decision-making. However, many applications such as personalized medicine and online advertising require the utilization of individual-specific information for effective learning, while user's data should remain private from the server due to privacy concerns. This motivates the introduction of local differential privacy (LDP), a stringent notion in privacy, to contextual bandits. In this paper, we design LDP algorithms for stochastic generalized linear bandits to achieve the same regret bound as in non-privacy settings. Our main idea is to develop a stochastic gradient-based estimator and update mechanism to ensure LDP. We then exploit the flexibility of stochastic gradient descent (SGD), whose theoretical guarantee for bandit problems is rarely explored, in dealing with generalized linear bandits. We also develop an estimator and update mechanism based on Ordinary Least Square (OLS) for linear bandits. Finally, we conduct experiments with both simulation and real-world datasets to demonstrate the consistently superb performance of our algorithms under LDP constraints with reasonably small parameters (ε, δ) to ensure strong privacy protection.

Key words: Contextual Bandits; Local Differential Privacy; Generalized Linear Model.

1. Introduction
2. Conclusion

Appendix

Appendix A: Proof of Results

A.1. Proof of Lemma

LEMMA 1. *As long as $t > 8\frac{d\log 9 + \log(T/\alpha)}{p_*^2}$, the following lower bound*

Proof of Lemma X $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ $\square$